Research on a Skin Color Detection Algorithm Based on Self-adaptive Skin Color Model

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Abstract—**Skin color detection is an important subject in computer vision research. Color segmentation takes a great attention because color is an effective and robust visual cue for characterizing an object from the others. To aim at existing skin color algorithms considering the luminance information not enough, a reliable color modeling approach was proposed. It is based on the fact that color distribution of a single-colored object is not invariant with respect to luminance variations even in the Cb-Cr plane and does not ignore the influence on luminance Y component in YCbCr color space. Firstly, according to statistics of skin color pixels, we take the luminance Y by ascending order, divide the total range of Y into finite number of intervals, collect pixels whose luminance belongs to the same luminance interval, calculate the covariance and the mean value of Cb and Cr with respect to Y, and use the above data to train the BP neural network, then we get the self-adaptive skin color model and design a Gaussian model classifier. The experimental results have indicated that this algorithm can effectively fulfill the skin-color detection for images captured under different environmental condition and the performance of the skin color segmentation is significantly improved.**

Keywords-skin color detection; skin color model; Gaussian model; skin color segmentation

I. INTRODUCTION

Color information is an important source of information during the human visual perception activities. Skin color is relatively concentrated and relative stabilization of region in the color image, and it is not to influence by shape, size and so on. In recent years, skin color detection has become a hot topic between domestic and foreign researchers, and great progress has been made in this field. Nowadays, skin color detection has many applications in tasks like detecting and tracking human faces and gestures, filtering web image contents and retrieving people in databases and Internet, even diagnosing diseases [1,2,3,4].

According to skin color's distribution characteristics on color space, skin color pixels can be detected quickly with skin color model. However it is difficult to detect skin color more accurately, because there exists many differences about skin color space distribution, which is affected by different race and different illumination [5].

Skin color characteristics are mainly described by skin color model. Usually, the skin color detection should be considered two aspects: color space selection and how to use the color distribution to establish a good skin color model. Nowadays main color spaces include RGB, HSV, TSL, YIQ, YCbCr, CIE-XYZ, CIE-Lab, CIE-Luv, YUV *et al.*

At present, the usual skin color detection Algorithms are mainly based on the color space of YCbCr. Current research mainly transforms the high relevance of color component in RGB color space to the small relevance of color component in YCbCr color space, Wang [6] removed luminance Y component information to establish Gaussian model. To reduce the effect of illumination, Y channel was not considered through out the segmentation process [7]. Mahmoud Elmezain et al. [8] ignored Y channel in order to reduce the effect of brightness variation and then use only the chrominance channels which are fully representing the color. They thought that luminance and chromaticity were explicitly separated, and the YCbCr color space was a favorable choice for skin detection. Thus the influence of luminance was ignored, these experiments were performed after neglect luminance Y information. And these skin color model only be used when the standard light source evenly exposures. Xu zhanwu et al. [9] used the ratio of infra-class to inter-class variance to prove the primary difference of skin color is luminance. To remove the luminance of 2d chrominance space, it increased the overlap degree of skin color and non-skin color, causing a bad classification performance.

So it is essential for robust color segmentation to make a color model adaptable to luminance changes. Especially, we can speed up color segmentation by making the color model in an off-line process before starting a real-time online visual task.

II. PROBLEM DEFINITION

This paper presents a new human skin color model in YCbCr color space. The Y, Cb and Cr components refer to Luminance, Chromatic blue and Chromatic red respectively. This is a transformation that belongs to the family of television transmission color spaces. This color space is used extensively in video coding and compression.

Given the triplet *RGB*, the YCbCr transformation can be calculated using formula (1).

A large amount of researchers have tried to separate luminance component from chrominance components of a color. Generally, Cb and Cr in YCbCr color space are not

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affected by luminance. Therefore, Cb and Cr in YCbCr model are independent of luminance, theoretically.

$$\begin{bmatrix} Y \\ Cb \\ Cr \\ 1 \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1140 & 0 \\ -0.1687 & -0.3313 & 0.5000 & 128 \\ 0.5000 & -0.4187 & -0.0813 & 128 \\ 0 & 0 & 0 & 1 \end{bmatrix} \bullet \begin{bmatrix} R \\ G \\ B \\ 1 \end{bmatrix} \quad (1)$$

To verify the experimental result, the image database in [10] is adopted in this paper. All the skin color sections are marked by masks. All the skin color pixels statistics are gathered from YCbCr color space. However, we have verified the fact that color distribution of a single-colored object is not invariant with respect to luminance variations even in the Cb-Cr plane through the experiments shown in Figure 1, which represents color distribution of skin color pixels under different luminance in the Cb-Cr plane. Each figure in Figure 1 shows color distribution for human skin color whose luminance level is different. The luminance of skin color increases from Figure 1 (a) to (f). If we ignore the luminance, the result is shown in figure 1(f), the horizontal and the vertical axis show Cb and Cr, respectively. From Figure 1, we know that Luminance Y components, to a certain extent, affect the Cb and Cr of skin color pixels. Therefore, there cannot be any local deformation or evolution of distribution, which is incorrect from Figure 1. So it is necessary for us to propose a strong robustness algorithm. Thus, we propose a reliable color modeling approach: Research on a Skin Color Detection Algorithm Based On Self-adaptive Skin Color Model, and do not ignore the influence on luminance Y component in YCbCr color space. Firstly, the skin color regions in the images were transformed from the RGB space to YCbCr space with skin color sections marked by masks. According to statistics, we take the luminance Y by ascending order and divide the total range of Y into finite number of intervals, N. Collect pixels whose luminance belongs to the same intensity interval and calculate the covariance and the mean value of Cb and Cr with respect to luminance Y, then we use the above data (the mean of each interval of Y, the covariance and the mean value of Cb and Cr) to train the BP neural network, getting the self-adaptive skin color model and then we designed the Gaussian model classifier. The training and learning of BP neural networks for skin color detection is mostly done offline in MATLAB. According to the luminance Y, we can detect skin color online and real-time, as shown in Figure 2.

Figure 1. Color distribution of human skin color in the Cb-Cr plane with respect to several luminance intervals (Y: luminance, 0-255).

III. GAUSSIAN MODEL

In this paper, according to Gaussian distribution of skin color, we adopt the 2D gauss model. Then the test image was transformed from the RGB space to YCbCr space. Through a large number of statistical and training methods, we get the Gaussian distribution center. According to the distance between the pixel and the center of Gaussian distribution, we get the skin's color likelihood, that is each pixel's skin probability.

This Gaussian function provides the probability that a pixel belongs to the skin class:

$$P(Cb, Cr) = \exp(-0.5(x-m)^T C^{-1}(x-m)) \quad (2)$$

Here m is the mean vector, $m = E(x)$, C is the covariance matrix, $C = E\{(x-m)(x-m)^T\}$, $x = (Cb, Cr)^{\mathrm{T}}$ represents the chrominance vector of an

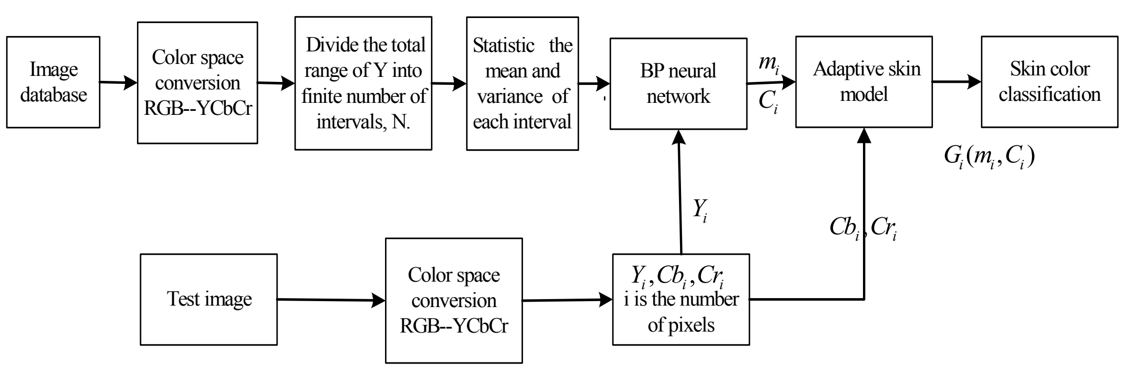

Figure 2. The basic architecture of the proposed work

input pixel.

Skin color Gaussian model $G(m,C)$ also expressed as:

$$m = (\overline{Cb}, \overline{Cr}) \tag{3}$$

$$\overline{Cb} = \frac{1}{N}\sum_{i=1}^{N} Cb_i \tag{4}$$

$$\overline{Cr} = \frac{1}{N}\sum_{i=1}^{N} Cr_i \tag{5}$$

$$C = \begin{pmatrix} \sigma_{CrCr} & \sigma_{CrCb} \\ \sigma_{CbCr} & \sigma_{CbCb} \end{pmatrix} \tag{6}$$

where, $\overline{Cb}$, $\overline{Cr}$ are the corresponding mean value of Cb, Cr, C is the covariance matrix .

IV. BP NEURAL NETWORK

A. definition of the input vectors and object vectors

During the training period, we take the luminance Y (0~255) by ascending order and divide the total range of Y into finite number of intervals, *N*. Collect pixels whose luminance belongs to the same intensity interval and calculate the standard deviation and the mean value of Cb and Cr with respect to Y, namely, m_i and C_i , Y_i is the mean value of the i^{th} interval of Y.

$$m_i = E\{x_{n_i}\} \tag{7}$$

$$x_i = [Cb_i, Cr_i]^{\mathrm{T}} \tag{8}$$

$$C_i = E[(x_i - m_i)(x_i - m_i)^T] \tag{9}$$

Here: $i = 1,2,\cdots,N$. n_i is the number of (Cb,Cr) which respect to the i^{th} interval of Y.

The discrete mathematics model $G_i(m_i, C_i)$ was established through the analysis of the statistics, corresponds to different Gaussian model in different luminance Y value, the number of Gaussian model is *N*, We take all the $[Y_i, G_i]$ as training samples for BP neural network. Y_i is used as the input variable of BP neural network, and the G_i is output variable. The BP neural network is used to fit data. Then we get the adaptive skin color model which respects to Y.

B. Design BP Neural Network

BP network can realize a special kind of nonlinear mapping and transform the input space into formative space by output, so we adopt 3-layer BP neural networks in this paper and the classified question becomes easy and feasible in the formative space by output. A input node correspond to the mean luminance Y of a interval, and the output node correspond to the skin modal parameters. Note that the parameters of BP neural networks have a great effect on the performance of BP neural networks and the number of node in hidden layers is the most important one among all the parameters. So our experiment only took the number of node in hidden layers into account. This number was adjusted several times and the best result was selected as the final evaluation of recognition performance.

In this paper, we use the empirical formula (10) to calculate the number of nodes in hidden layer as a starting value. Here M is the number of node input layer.

$$n = \log_2 M \tag{10}$$

Train the BP neural network, and record the convergence time, then the number of node in hidden layer, add 1; then we need to train the BP neural network again, record the convergence time again, when the convergence speed kept relatively stable, this value is the most appropriate number of node in hidden layer.

It is important to design neural network excitation function for networks convergence. In this paper, obviously, the sigmoid activation function can be selected for the hidden layer and the output layer. The input vectors are normalized by the function (11).

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{11}$$

V. SKIN COLOR CLASSIFICATION

Each skin pixel probability was identified using the following equation:-

$$P(x_i) = \exp(-0.5(x_i - m_i)^T C_i^{-1}(x_i - m_i)) \tag{12}$$

Firstly, a unitary processing for *P(x)* was made. Namely, each *p(x)* divides the maximum value of all the *P(x)*, it make each *p(x)* between 0 and 1, and the luminance of skin region becomes a more prominent, the greater the value of *p(x)* is, the greater skin possibility is. On the contrary, the possibility is smaller. So the classification rule of Gaussian model can be determined as follows:

$$\begin{cases} P(x) > T & \text{x is skin color pixel} \\ P(x) < T & \text{x is non-skin color pixel} \end{cases} \tag{13}$$

Threshold value *T* can be adjusted according to the experiment. With too large *T*, the Detection Rate *(DR)* and False Positive Rate *(FPR)* will be reduced, while False Negative Rate *(FNR)* will increase too; with too small *T*, it will result in both enlarged *DR* and *FPR*. Thereby, *T* should be selected as a compromise between *DR* and *FNR* in this paper.

VI. EXPERIMENT RESULTS AND ANALYSIS

The skin color detection method presented in this paper is developed, trained and tested using MATLAB7.6. To verify the algorithm above, the database in [10] is adopted in this paper. The database contains 3792 skin-color images with their skin color sections are marked by masks manually and 8964 non-skin-color images. This image database covers a wide spectrum of environmental conditions, such as luminance, which can guarantee that possible area of skin color distribution will be overspread in all environmental conditions, so it is ideal to verify all kinds of skin-color detection algorithm.

All of the experiments were performed after passing the data through the same preprocessing stage, except for minor differences that were necessary according to the experimental context. The evaluation of detection methods and comparative results are based mainly on calculating the detection rate, false positive ratio, and false negative ratio. They are given by:

$$\textit{Detection Rate (\%)} = \frac{N_S}{N_F} \times 100 \qquad (14)$$

$$\textit{False Positive Rate (\%)} = \frac{N_{FP}}{N_{NF}} \times 100 \qquad (15)$$

$$\textit{False Negative Rate (\%)} = \frac{N_{FN}}{N_F} \times 100 \qquad (16)$$

In these equations, N_F is the total number of skin color pixels; N_S is the number of correctly detected skin color pixels; N_{NF} is the total number of non-skin color pixels; N_{FP} is the number of non-skin pixels that are detected incorrectly as skin color, and N_{FN} is the number of skin color pixels that are detected incorrectly as non-skin color pixels.

Calculating the frequency of each skin color spot in YCbCr color space and weeding out 5% skin color spots with lower frequency, we conduct experiments for skin color segmentation, and train the BP neural network by using the data *(Y,G)*,when *N*=5. First we must transform the input image RGB values to YCbCr colorspace using (1). We send the luminance Y component to the trained neural network, then we obtain the parameters of Gaussian distribution: m_i and C_i ,namely $G(m_i, C_i)$, where m_i and C_i represent the mean vector and the covariance matrix with respect to i^{th} pixel in the input image, thus we get probability of the i^{th} pixel by using the equation(12).

After all the pixels of the input image simulation, we obtain comparatively accurate similarity of image. The p(x) probability can be used to measure the similarity of the skin color pixels.

So each pixel is classified as skin or non skin by using (13). We set a global threshold *T* automatically by the Otsu-method [11] which finds the threshold by optimizing a measure of separability on the analyzed histogram. Then we calculate the DR, FPR and FN respectively. Similarly, when N=15, 25, 35, 45, 55, 65, 75, …, 285, 295,300 respectively, we conduct experiments separately and *DR*、 *FPR*、 *FNR* are calculated separately. *DR*、*FNR* and *FPR* are shown by curves with ‘*’ ‘+’ ‘o’ respectively in Figure 3.

From Figure 3, we know when *N* is smaller, trained the

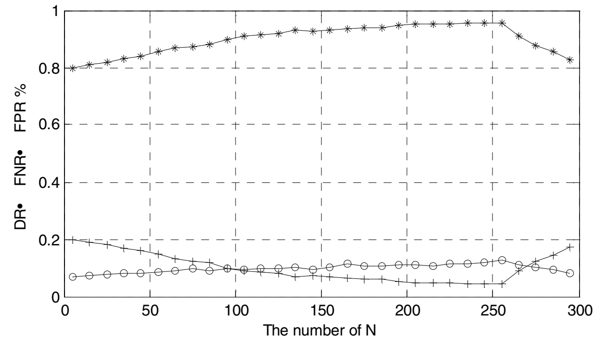

Figure 3. The curves of DR, FNR and FPR

BP neural network by using the data respect to *N*, we find that the data have no regularity and no statistic, especially, are significantly influenced by the noise, thus the skin color identification performance corresponding to the *N* has been reduced to some extent. When *N* is larger, DR declines rapidly. It is because that all the pixels collected which belong to the same intensity interval is very small in quantity, making noise in proportion of the relatively increase. In each interval, the data have no generality and no statistic, thus the skin-color identification performance has been reduced to some extent. So when we choose a proper *N* and threshold T, the experimented results show that it has good effect of color image segmentation, we conduct experiments with *N* = 255, threshold T= 0.45 the number of node in hidden layer n=50, the results are shown in the Figure 4.

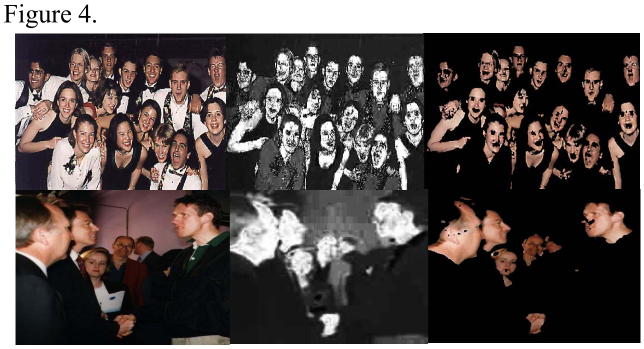
Figure 4. Skin-color detection results with our method

The two row images from left to right are original image, likelihood image, skin color detection image respectively. The first row in Figure 4 shows the experimental results with single background and uneven luminance. The pictures in the second and the third rows refer to images to be detected, because the image scene is complicated and the noise interference is severe, the non-skin color areas similar to skin-color pixels exist, which causes a fraction of wrongly detected pixels. But generally, most of skin-color areas have been detected successfully.

Table I gives the performance comparison result between the algorithm in this paper and other algorithms with threshold values properly selected. According to this comparison result, we can conclude that its recognition performance has improved significantly by using the Self-adaptive skin model which we proposed.

TABLE I. SKIN-COLOR RECOGNITION PERFORMANCE COMPARISON AMONG DIFFERENT ALGORITHMS

Recognition rate / Methods	DR	FNR	FPR
The method in this paper	96.01%	3.99%	15%
Wang Jinting et al.[12]	91.436%	16.968%	14.805%
Qiang zhu et al. [13]	92 %	8%	30%
R.Hassanpour et al. [14]	93%	7%	33%

VII. EXPERIMENT RESULTS AND ANALYSIS

Skin color has been proven to be a useful and robust cue for face detection, 1ocalization and tracking. Naked skin region is one of the most important features to detect the erotic pictures. The statistics of skin color distribution were obtained in YCbCr color space. We have presented a skin color detection algorithm for color image using a self-adaptive skin color model which depends on the luminance Y, so as to overcome the influence of luminance Y. It is based on the fact that color distribution of a single-colored object is not invariant with respect to luminance variations even in the Cb-Cr plane. This method can fit under wider light condition, and it's also effective to detect skin color regions from the color images with complex background. The experimental result has indicated that the approach in this paper has a preferable robustness and the skin-color detection performance is improved significantly.

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