Face Detection via Color and Edge Information

Ravi Verma
Department of Computer Science, Research Scholar, CMJ University
Shillon, India
E-mail: forever_ravi123@yahoo.co.in

Harish Kumar Shakya
Department of Computer Engineering, Research Scholar, IIT- BHU
Varanasi, India
E-mail: hkshakya.rs.cse@itbhu.ac.in

Abstract

In this paper, an algorithm for segmenting skin regions in color images using color and edge information is presented. Skin colored regions are first detected using a Bayesian model of the human skin color. These regions are further segmented into skin region candidates that satisfy the homogeneity property of the human skin. We show that Bayesian skin color model outperforms many other models such as the piece-wise linear models, Gaussian models and model based on multilayer perceptions. Experimental results indicate that the proposed segmentation algorithm reduces false detection caused by background pixels having skin colors, and more significantly it is capable of separating true skin regions from falsely detected regions.

Keywords: Skin color, Segmentation regions, Face detection and Skin color model.

1. Introduction

Face detection is a well-known pattern recognition problem. Such task is the first fundamental step for many applications such as face recognition and 3D face reconstruction. Although many approaches have been proposed over the last few years, it still remains a very challenging problem today [1] [2] due to significant face appearance variations, such as pose (front, non-front), occlusion, image orientation, lighting conditions and facial expression. In recent years, there has been a growing research interest in the problem of segmenting skin regions in color images. Skin segmentation aims to locate skin regions in an unconstrained input image. It plays an important role in many computer vision tasks such as face detection [6, 7and 9], face tracking [1], hand segmentation for gesture analysis, and filtering of objectionable Web images [5]. In these tasks, results of skin segmentation enable subsequent object detection to focus on reduced skin regions instead of the entire input image.

To this end, skin segmentation is a very effective tool because skin regions can be located fast with usually minimal amount of added computation. Most existing skin segmentation approaches are based on skin color. Skin regions are detected by looking for pixels that have skin colors. In this paper, we propose an algorithm that combines color and edge information to segment skin regions in color images. The presence of skin colors in the input image are first detected using a skin color model based on the Bayesian decision rule for minimum cost and nonparametric density estimation. The detected skin-colored regions are then refined using homogeneity property of the human skin. The paper is organized as follows. The Bayesian skin color model is described in Section 2. The proposed skin segmentation algorithm is addressed in Section 3. Analysis of the Bayesian skin color model and the proposed segmentation algorithm are presented in Section 4. Concluding remarks are given in Section 5.

2. Human Skin Color Model

A human skin color model is used to decide if a color is a skin or non skin color. Major requirements of a skin color model are listed below:

- *Very low false rejection rate at low false detection rate.*

Skin color detection is first step in skin segmentation; therefore it is imperative that almost all skin colors are detected while keeping the false detection rate low. False detections can be handled later when more *apriority* knowledge about the object of interest (ie. face, hand) is available.

- *Detection of different skin color types.*

There are many skin color types, ranging from whitish and yellowish to blackish and brownish, which must be all classified in one class, skin color.

- *Handling of ambiguity between skin and non skin colors.*

There are many objects in the environment that have the same color as skin. In these instances, even a human observer cannot determine if a particular color is from a skin or non skin region without taking into account contextual information. An effective skin color model should address this ambiguity between skin and non skin colors.

- *Robustness to variation in lighting conditions.*

Skin color can appear markedly different under different lighting. It is impractical to construct a skin color model that works under all possible lighting conditions. However, a good skin color model should exhibit some sort of robustness to variations in lighting conditions. In our work, we aim to create a skin color model for typical office lighting and daylight conditions. A human skin color model requires a color classification algorithm and a color space in which colors of all objects are represented. Existing classification algorithms include multilayer perceptions [11], self-organizing maps [2], linear decision boundaries [3, 6, 13], and probabilistic classifiers based on density estimation [8, 9]. The choice of color space is also varied: RGB [8], YCbCr [3, established technique in statistical pattern classification (cf. [4]). This technique has been used by a number of authors for skin and non skin color classification in the YCbCr and RGB color spaces [8]. In this paper, we analyze the performance of the Bayesian model in several color spaces, namely RGB, CIE XYZ, HSV, YCbCr and CIE Lab.

In addition, we compare the two classification approaches: one using only chrominance components of a color and the other using all components. We also study the effect of the histogram size on the accuracy of skin and non skin color classification. Results of these studies enable us to create a Bayesian skin color model that is efficient in terms of memory storage, classification accuracy and speed. The Bayesian model can be described as follows. Let c be a color vector in a given color space. Let $p(\mathrm{c}|skin)$ and $p(\mathrm{c}|nonskin)$ be the class-conditional probability density functions (pdfs) of the skin color and non skin color classes, respectively. The color c is classified as skin color if:[9,10] HSV [13], CIE Luv, Farnsworth UCS, and normalized RGB [12]. The human skin color model used in our work is based on the Bayesian decision rule for minimum cost, which is an

$$\frac{p(\mathrm{c}|skin)}{p(\mathrm{c}|nonskin)} \geq \theta, \qquad (1)$$

Where θ is a threshold. The left term of (1) is known as the likelihood ratio. The theoretical value of θ that minimizes the classification cost is determined by *a priori* probabilities $P(skin)$ and $P(non\ skin)$ of the two classes (cf.[4]):

$$\theta = \frac{\lambda_{fd} \quad \mathrm{P(nonskin)}}{\lambda_{fr} \quad \mathrm{P(skin)}} \qquad (2)$$

Here, λfd and λfr are the costs of false detection and false rejection, respectively. The cost of a correct classification is assumed to be zero. In our work, the value of θ is determined experimentally.

The histogram technique is employed to estimate the class-conditional pdfs of skin and non skin colors. This technique is viable in our case because the dimension of the feature vector c is low (at most 3), and a large set of skin and non skin colors can be collected. It can be described as follows. From a set of labeled skin and non skin pixels, we obtain two histograms Hskin(c) and Hnonskin(c), which are the counts of skin and non skin pixels having a value c, respectively. The class-conditional pdf values are estimated by simply normalizing the histograms:

$$P(C|skin) = \frac{H_{skin} \quad (C)}{\sum_C H_{skin} \quad (C)} \qquad (3)$$

$$P(C|non\ skin) = \frac{H_{non\ skin} \quad (C)}{\sum_C H_{non\ skin} \quad (C)} \qquad (4)$$

These values are then used in (1) to discriminate between skin and non skin colors. A comprehensive investigation of the Bayesian model and other skin color models will be reported in Section 4.

3. Skin Segmentation Algorithm

3.1 Rationales of the Proposed Approach

So far, skin detection has been performed pixel-wise and used only the color information of individual pixels. Experimental results in Section 4 have indicated that the Bayesian skin color model is very accurate in detecting skin colors. However, pixel-wise color segmentation is not sufficient for skin detection purpose because pixels in the image background (i.e. Non skin pixels) may also have skin colors and this leads to false detection. Another issue is that the true skin regions may be blended with the nearby skin-colored background, and this can have an adverse effect on subsequent processing of skin regions. There is a clear need to reduce the amount of false detections and to separate true skin regions from possible false detection. The segmentation approach described in this paper is an extension of the segmentation algorithm we developed in [10], in which localized skin color thresholds θ are determined for each image region using

edge-based region homogeneity measures. Our observation is that the human skin has a special texture that is formed by the grouping of pixels having similar colors, and consequently skin regions exhibit a strong homogeneity. Therefore, non homogenous skin colored regions should be removed. Furthermore, we discover that even when the background region close to a skin region has skin color, there always exists a boundary between the true skin region and the background. The key idea of the proposed approach, therefore, is detecting such boundary using edge detectors, and subsequently removing boundary pixels from the skin map.

3.2 Segmentation Algorithm

The steps of the proposed skin segmentation algorithm are described below.

Steps 1-2 are for skin color detection, Step 3-4 are for skin segmentation using edge and color. Step 5-6 are post-processing.

Step 1: Generate the skin color score image S by computing the skin color likelihood ratios for all image pixels of the color input image I. apply an averaging filter (size 3X3) to smooth the skin color score image.

Step 2: Threshold the skin color score image as in (1) to obtain a binary map Bc for skin colored regions. A low threshold $\theta = 0.8$ is used.

Step 3: Apply edge detectors (Sobel and Canny) on the color channels of the input image to find edge pixels. We find that the Canny edge detector is suitable for detecting strong edges between homogenous regions whereas the Sobel edge detector is better at detecting non-homogenous blocks within a skin-colored region.

Step 4: For each region in Bc, raise the skin color threshold iteratively by a factor of 1.2 until the standard deviation (*std*) σ of the region intensity or the ratio of the edge count and the area of the region are below predefined thresholds [10]. In addition, if the standard deviation measure σ of the region is higher than a threshold, all edges pixels (found in step 3) are removed from the region binary map.

Step 5: Remove regions that are smaller than 1% of the largest region, and regions whose area is reduced to less than 5% after a morphological erosion operation.

Step 6: Repeat the steps below for each remaining region, which is represented by binary map B*i*

- Find the convex hull Bconv, *i* of the region.
- Find the part of the skin color map Bc that corresponds to the convex hull. Let Bcolor, *i* denote this part.
- Obtain the final binary map for the skin region: B*i* (*final*) = Bconv, *i* AND Bcolor, *i*.

4. Results and Analysis

4.1 Analysis of the Bayesian Skin Color Model

The data used in this work are taken from the *ECU face detection database* that we have constructed at Edith Cowan University. The database consists of over 3,200 color image (Set 1); to the best of our knowledge, it is one of the largest databases that support the many tasks involved in color-based human face detection. All the images in the database have been manually segmented for skin regions (Set 3) and face regions (Set 2). From the ECU face detection database (images 1-2500), we extracted a training set of 116.6 million skin pixels and 564.7 million non skin pixels. Different skin types including blackish, whitish, yellowish and brownish (under moderate lighting conditions) were included in the set.

The Bayesian skin color model were applied on a test set of 500 images (images 2501-3000) to detect skin, and the outputs were compared pixel-wise with the manually segmented skin images. In our experiments, five different color spaces: RGB, CIE XYZ, HSV, YCbCr, and CIE Lab, and histogram sizes of 256, 128, 64, 32, 16 and 8 bins per color channel were analyzed. The classification approach that uses only chrominance channels (ie. HS, CbCr, and ab) was also tested. Due to space limitations, only part of the results is shown in Figs 1-3 and Table 1. Major findings of our comparative study are listed below:

- There is *no* difference in the performance of the five main color spaces (RGB, CIE XYZ, HSV, YCbCr, and CIE Lab) at histogram sizes greater than 128 (and up to 256) bins per channel (Fig. 1).
- Regardless of the histogram size and the color space, classification using *all* color channels consistently outperforms classification using *only* chrominance channels (Fig. 1).
- The classification performance of the proposed Bayesian model remains *almost constant* in the RGB color space, for histogram sizes between 32 and 256 (Fig. 2). In comparison, the classification performance for other color spaces degrade rapidly as the histogram size drops below 64.
- The Bayesian model using nonparametric density estimation (i.e. histogram technique) is superior to the other models such as the fixed-range model [3], piecewise linear model [6], Gaussian model [9], model based on the MLP classifier [11] in terms of classification accuracy (Fig. 3). The classification

rates of the Bayesian classifier in the RGB color space (64 bins) for different threshold values are given in Table 1.

4.2 Analysis of Skin Segmentation Algorithm

The Bayesian skin color model in the RGB color space, with a histogram size of 64, which requires 2MB of memory, was used for skin color detection. However, analysis in subsection 4.1 shows that the Bayesian skin color model can be applied to any color space with good results.

Sample results of skin color detection and skin segmentation on two test images are shown in Fig. 4. All skin colors in the input image are detected by the Bayesian skin color model (Fig. 4c-d). However, background pixels having skin color are also picked up (including some near the actual skin regions Fig. 4d). Results in Fig. 4e-f show that the proposed segmentation algorithm reduces false detections significantly. More importantly, the actual skin regions are separated from false detections nearby. This property is very desirable in tasks such as face detection because each output skin region is homogenous and this makes detecting facial features more reliable. Although uniform backgrounds such as wooden surfaces or painted walls will be detected, these false detections can be easily discarded during face detection due to lack of facial features enclosed in the regions.

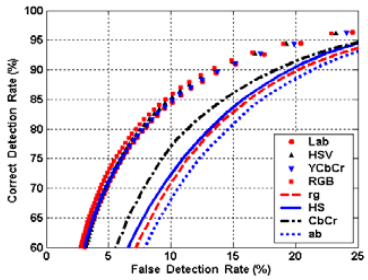


Figure 1: The Bayesian model in five *color spaces* and three *chrominance planes* (histogram size = 256).

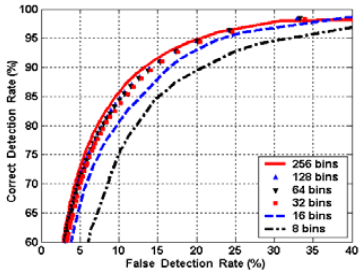


Figure 2: The Bayesian model at different histogram sizes (color space = RGB).

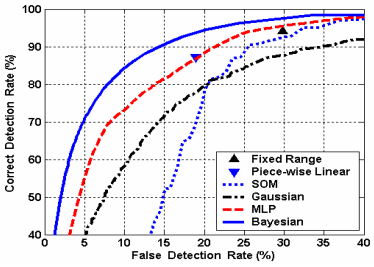


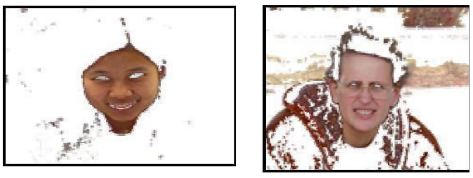
Figure 3: Comparison of skin color models.

Table 1: Skin segmentation using only skin color.

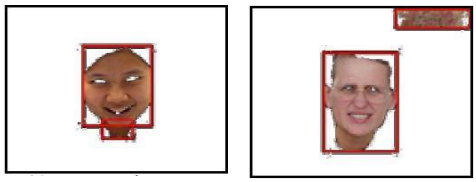
	$\theta = 1$	$\theta = 2$	$\theta = 42^*$
Correct detection rate	91.0%	84.4%	74.0%
False detection rate	15.3%	10.0%	5.8%
Classification rate	86.1%	88.7%	89.8%

*Threshold at which classification rate is maximum.

(a) Input image (b) Input image



(c) Skin color detection (d) Skin color detection



(e) Segmentation ouput (f) Segmentation ouput

Figure 4: Skin color detection and skin segmentation.

5. Conclusions

We presented a skin segmentation algorithm that combines both color and edge information. In the proposed algorithm, skin-colored regions are detected using a very accurate skin color model based on the Bayesian decision rule for minimum cost and nonparametric density estimation. The detected regions are further processed using the homogeneity property of the human skin. The proposed segmentation algorithm is shown to be capable of reducing false detection caused by skin colored image background, and separating actual skin regions from many false detection. We also reported a comprehensive analysis of the Bayesian skin color model together with several interesting results.

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