

# High-speed Skin Color Segmentation for Real-time Human Tracking

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**Abstract**—This paper proposes an original low-complex image classification technique for fast skin color segmentation proper for human face and limbs tracking. Experimental results demonstrate promising performance achievements compared to other existing skin color segmentation methods. Furthermore, the simplicity of this method is an attractive feature for real-time applications. The proposed method is independent of skin distribution shape and unlike the majority of techniques does not require exhaustive training.

## I. INTRODUCTION

SKIN color is often the first feature used for localization of human face and hands in high level tracking systems because it allows fast processing and it is invariant to geometric variations of the face pattern. Skin color detection has extensively been adopted in different applications including security systems, multimedia, intelligent transportation, medical diagnostics, human-computer interaction, video compression, content-based indexing and retrieval systems.

There are assorted techniques in literature [1]-[4] addressing skin color as a cue for human detection. They have adopted different color spaces and various skin modeling techniques; however, only a few of them are suitable to be used in real time tracking systems. One of the most important properties of a real time skin color detector for human tracking is its timing complexity. It also should have low false positive and false negative rates.

We start with a brief preview of the existing skin color segmentation methods in today's literature and then introduce an original scheme for skin color classification that is suitable for real time human tracking applications. This method is fast, requires little memory storage and is independent to skin color distribution shape. Furthermore, in the proposed method the requirement for any exhaustive training is eliminated. In the experiment reported here, we compare the proposed method with four typical skin color modeling methods in five different color spaces. The efficiency of our method is then confirmed by several experimentations on numerous real images including CVL face database.

The organization of the paper is as follows: Section 2 provides a brief preview of skin color distribution models and related color spaces. Section 3 overviews the proposed method. Experimental results and comparative evaluation

studies are provided in Section 4, and Section 5 concludes the paper.

## II. PREVIEW OF SKIN COLOR DISTRIBUTION MODELS

Skin segmentation can be divided into three major groups: region-based, parametric and nonparametric skin distribution modeling methods [5]. Nonparametric methods are histogram-based, and estimate the skin color distribution from the training data without considering an explicit model for skin color. Parametric methods approximate skin color distribution with a single or a mixture of Gaussian distributions that provide the ability to interpolate and generalize the incomplete training data.

### A. Color spaces

The color spaces adopted in this paper for comparison reasons including HSV/HSI, RGB, TSL and YCrCb are popular color spaces used in literature for skin color detection and classification. The RGB color model is an additive model in which red, green and blue light are combined in various ways to reproduce other colors. Hue and saturation values in Hue-saturation based color spaces are computed from R, G and B values,

$$H = \arccos \frac{\frac{1}{2}((R-G)+(R-B))}{\sqrt{((R-G)^2 + (R-B)(G-B))}}$$

$$S = 1 - 3 \frac{\min(R, G, B)}{R + G + B}$$

The intensity, lightness or value is related to the color luminance defined as,

$$V = \frac{1}{3}(R + G + B)$$

A normalized chrominance-luminance TSL space is a transformation of the normalized RGB into more intuitive values, close to hue and saturation in their meaning,

$$S = \sqrt{9/5(r'^2 + g'^2)}$$

$$T = \begin{cases} \arctan(\frac{r'}{g'}) / 2\pi + 3/4 & \text{if } g' < 0 \\ \arctan(\frac{r'}{g'}) / 2\pi + 1/4 & \text{if } g' > 0 \\ 0 & \text{if } g' = 0 \end{cases}$$

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$$L = 0.299R + 0.587G + 0.114B$$

where  $r' = r - 1/3$ ,  $g' = g - 1/3$  and

$$r = \frac{R}{R+G+B} \quad g = \frac{G}{R+G+B}$$

In normalized RGB color space. Finally, YCrCb is an encoded nonlinear RGB signal. Color is represented by luma (which is luminance, computed from nonlinear RGB), constructed as a weighted sum of the RGB values, and two color difference values  $C_r$  and  $C_b$  that are formed by subtracting luma from RGB red and blue components.

$$Y = 0.299R + 0.587G + 0.114B$$

$$C_r = R - Y$$

$$C_b = B - Y$$

The transformation simplicity and explicit separation of luminance and chrominance components makes this color space attractive for skin color modeling.

### B. Region-based models

Actual measurements have shown that dark, yellowish and pale skin colors have almost the same chromaticity [3]. It is also shown in [6] that the chromaticity of skin follows a curve similar to the Planckian locus under light sources of different correlated color temperatures. Therefore, the region containing trained samples of skin color pixels belong to different races and under various illumination conditions is called skin locus. This method is suitable for skin color detection in images or preprocessing of human tracking, however it cannot be applied directly for real time human tracking purposes because it detects all types of skin tones and cannot distinguish between people moving in front of the camera in tracking scenarios. Other region-based methods including [7] define different boundary rules for skin tone region in different color spaces.

### C. Two-dimensional or three-dimensional single Gaussian models

In these methods skin color distribution is approximated by 2D or 3D Gaussian distribution and is modeled by Gaussian joint probability distribution function (pdf). For instance, joint probability density function in normalized RGB color space is defined as,

$$P((r, g) | skin) = \frac{1}{2\pi |\Sigma_s|^{1/2}} \cdot e^{-\frac{1}{2} \begin{bmatrix} r-\bar{r} \\ g-\bar{g} \end{bmatrix}^T \Sigma_s^{-1} \begin{bmatrix} r-\bar{r} \\ g-\bar{g} \end{bmatrix}}$$

where

$$\bar{r} = \frac{1}{n} \sum_{j=1}^n r_j \quad \bar{g} = \frac{1}{n} \sum_{j=1}^n g_j$$

$$\Sigma_s = \begin{bmatrix} \sigma_r^2 & \sigma_{rg} \\ \sigma_{rg} & \sigma_g^2 \end{bmatrix}$$

are mean and covariance matrix and  $n$  is the total number of the sample pixels collected from a skin patch of the person being tracked, and

$$\sigma_r^2 = \frac{1}{n-1} \sum_{j=1}^n (r - \bar{r})(r - \bar{r})^T$$

$$\sigma_{rg}^2 = \frac{1}{n-1} \sum_{j=1}^n (r - \bar{r})(g - \bar{g})^T$$

Skin segmentation can be performed based on the probability density function value directly as a probability of each observed pixel belonging to the person being tracked. Another choice is measuring the mahalanobis distance defined for normalized RGB color space as

$$D = \begin{bmatrix} r-\bar{r} \\ g-\bar{g} \end{bmatrix}^T \Sigma_s^{-1} \begin{bmatrix} r-\bar{r} \\ g-\bar{g} \end{bmatrix}$$

From the color pair or triads to mean vector.

### D. Two-dimensional or three-dimensional multiple or mixture of Gaussians models

Skin color distribution is approximated with a higher complexity model named multiple or mixture of Gaussians modeling. This method can more precisely approximate skin color distribution especially if it contains face, lips, eyes or hair color in head tracking systems for instance. Multiple or mixture of Gaussians modeling has a high computational complexity that increases with the number of probability density functions considered for modeling. This distribution is defined by

$$P((r, g) | skin) = \sum_{j=1}^k \pi_j \cdot P_j((r, g) | skin)$$

with mixing properties  $\pi_j$  and  $K$  component number between two to sixteen.

Lee et al. [8] also proposed a new statistical color model for skin detection by changing the position of mean vector, after considering only distinctive sample colors. Due to asymmetry of the skin cluster with respect to its density peak, usage of this method can hopefully lead to lower false positives rate.

### E. Histogram-based models

In non-parametric skin modelling methods skin color distribution is estimated from the training data without deriving an explicit model such as Gaussian for the skin color

distribution. Non-parametric skin modelling methods are all histogram based. After reading an image or frame, the color values are quantized into a number of bins, each corresponding to particular range of color component value pairs (in 2D case) or triads (in 3D case). These bins, forming a 2D or 3D histogram are referred to as the lookup table (LUT). Each bin stores the number of times this particular color occurred in the training skin images. After training, the histogram counts are normalized, converting histogram values to discrete probability distribution  $P(\text{skin} | (r, g))$  in normalized RGB color space for instance.  $P(\text{skin} | (r, g))$ , can be computed using Bayes equation, maximum likelihood (ML) or maximum a posteriori (MAP) Bayes rules. After some manipulation [5] the Bayes equation

$$P(\text{skin} | (r, g)) = \frac{P((r, g) | \text{skin}) \cdot P(\text{skin})}{P((r, g) | \text{skin}) \cdot P(\text{skin}) + P((r, g) | \neg \text{skin}) \cdot P(\neg \text{skin})}$$

is simplified to

$$\frac{P(\text{skin} | (r, g))}{P(\neg \text{skin} | (r, g))} > \text{Threshold}$$

where

$$\text{Threshold} = K \frac{1 - P(\text{skin} | (r, g))}{P(\text{skin} | (r, g))}$$

Color values greater than threshold belong to skin.

### III. THE PROPOSED METHOD

This method takes a skin patch from the target person, and the maximum counted color in that region is obtained. If  $\mathbf{S}$  is a skin patch from the target person,

$$\mathbf{S}_c = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1i} \\ c_{21} & c_{22} & \dots & c_{2i} \\ \vdots & \vdots & \ddots & \vdots \\ c_{j1} & c_{j2} & \dots & c_{ji} \end{bmatrix}$$

and  $c_{ij}$  is the color value of each pixel in the patch, then

$$\mathbf{S}_R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1p} \\ r_{21} & r_{22} & \dots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{q1} & r_{q2} & \dots & r_{qp} \end{bmatrix} \quad \mathbf{S}_G = \begin{bmatrix} g_{11} & g_{12} & \dots & g_{1p} \\ g_{21} & g_{22} & \dots & g_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ g_{q1} & g_{q2} & \dots & g_{qp} \end{bmatrix} \quad \mathbf{S}_B = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1p} \\ b_{21} & b_{22} & \dots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{q1} & b_{q2} & \dots & b_{qp} \end{bmatrix}$$

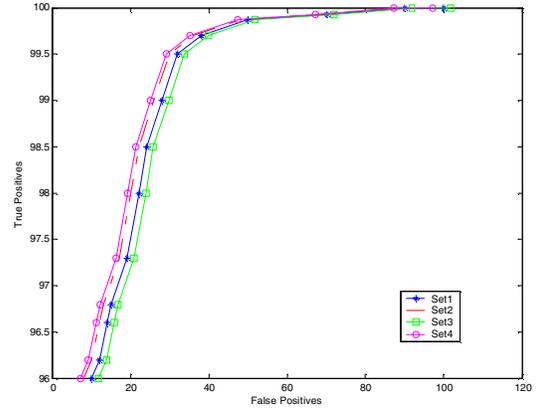


Fig. 1. ROC curve for four sets of images for obtaining the best compromise threshold value

are matrices of red, green and blue values for each pixel color in that patch. We also define RGB values of the whole image as,

$$\mathbf{I}_R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \quad \mathbf{I}_G = \begin{bmatrix} g_{11} & g_{12} & \dots & g_{1n} \\ g_{21} & g_{22} & \dots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \dots & g_{mn} \end{bmatrix} \quad \mathbf{I}_B = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \dots & b_{mn} \end{bmatrix}$$

where  $m \geq q$  and  $n \geq p$ . Now if  $r_0$ ,  $g_0$  and  $b_0$  are red, blue and green values of the most repeated color in the skin patch, then subtracting  $r_0$ ,  $g_0$  and  $b_0$  from all RGB values of the image will provide,

$$\delta r_{ij} = |r_{ij} - r_0|$$

$$\delta g_{ij} = |g_{ij} - g_0|$$

and

$$\delta b_{ij} = |b_{ij} - b_0|$$

for  $i \in \{1, 2, \dots, m\}$  and  $j \in \{1, 2, \dots, n\}$ . Now we define two new parameters,

$$\delta_{ij} = \max(\delta r_{ij}, \delta g_{ij}, \delta b_{ij})$$

$$\eta_{ij} = \max(r_{ij}, g_{ij}, b_{ij})$$

$$\forall i \in \{1, 2, \dots, m\} \text{ and } j \in \{1, 2, \dots, n\}$$

where  $\eta_{ij}$  is the maximum color value in the image. If all the colors are normalized into values between 0 and 1, then  $\eta_{ij}$  usually has a value of 1. We also define

$$\Delta_{ij} = \eta_{ij} - \delta_{ij}$$

where  $\Delta_{ij}$  is a boundary value for each pixel. If  $\Delta_{ij}$  is greater than a specific threshold, the color of the selected pixel belongs to the skin distribution. The threshold value of 0.89 is

obtained from the ROC (receiver operating characteristic) curve—tested for various sets of images. Figure 1 illustrates the ROC curve for four different sets of images.

#### IV. COMPARATIVE EVALUATION AND EXPERIMENTAL RESULTS

We have tested this method on several images, including CVL face database with a set of 798 images containing 114 people. The performance of the proposed method was promising when compared to state-of-the-art skin color detectors. Figure 2 provides the result of applying different skin detectors to a sample image. Skin locus detects any color similar or close to skin color, such as wood in an image, that belongs to the training sample. Therefore, it is not suitable for the purpose of face tracking because an efficient skin color detector for tracking systems should be able to distinguish between the person being tracked and other people or objects with similar skin color in the background. However, skin locus can be used as a filter for pre-processing purposes before face detection and tracking. Parametric and non-parametric methods produce similar performance results. Figure 2 reveals our fast, low-complex method to be superior to other methods in detecting skin color pixels related to the desired person. Generally, nonparametric or histogram-based methods are fast, independent to distribution shape and color space selection, but they require excessive storage memory and proper training. Parametric skin distribution modeling techniques have the ability to interpolate incomplete training, and require very little memory, but they are slow—especially in the case of multiple or mixed Gaussians. They are distribution shape-dependent, and have a higher false positive rate. The proposed method is very fast compared to previously mentioned methods. It requires minimum storage memory and is independent of distribution shape.

The proposed method has been also tested in various color spaces such as RGB, HSV, HIS, TSL and YcrCb—all used in the literature for skin classification. Experimentation has provided satisfactory results in the above color spaces. The best performance, however, is for HSV/HIS and RGB color spaces. Figure 3 is a sample of skin color detection results for the proposed method, as applied to an image in different color spaces. A whole face tracker has also been implemented, based on the method proposed in this paper. Implementation details and experimental results are explained in [9]. As a result, the proposed technique is faster than other skin classifiers and, unlike histogram-based techniques, needs minimum memory storage. This scheme also has a low false positive rate—unlike Gaussian modeling methods—because it is independent to distribution shape and does not require any exhaustive prior training.



Fig. 2. Skin color detection techniques comparison (Original image, Skin locus, histogram, Single Gaussian, elliptic boundary and proposed method)

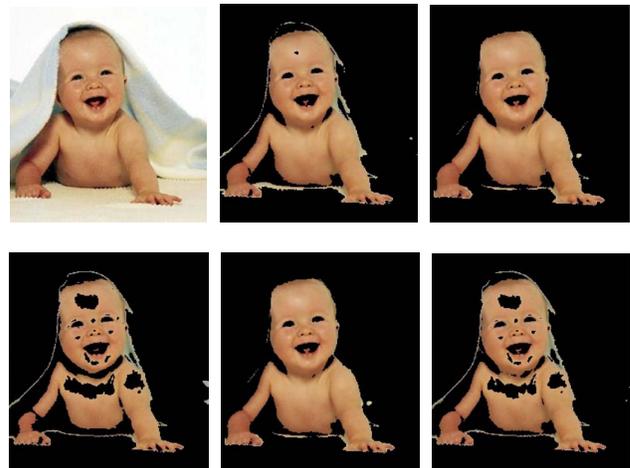


Fig. 3. Proposed skin color classification tested in different color spaces (Original image, RGB, HSV, TSL, HIS and YcrCb color spaces)

#### V. CONCLUSION

In this paper different methods for skin color segmentation and modeling in today's literature were studied, implemented and compared. A new method was then proposed that is proved to be simple and efficient. This technique is the fastest among all algorithms implemented and unlike histogram based techniques needs little memory storage and, in contrast with Gaussian modeling methods has low false positive rate. It is independent to distribution shape and does not require any exhaustive prior training. Experimental results confirm that in spite of its simplicity, the proposed method performs effectively in practice. It has been tested on various images including CVL face data base and finally been adopted as part of a face tracker system.

## VI. ACKNOWLEDGMENT

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