Pixel-based Skin Detection Based on Statistical Models

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***Abstract*—Skin detection is a preliminary step in many machine vision applications. In this paper, we propose applying the Gamma, Beta, and Laplace distributions for modelling skin color pixels in arbitrary chromaticity spaces used for parametric skin detection. Since the proposed distributions do not inherently consider the correlation between the chromaticity components, a method to eliminate the correlation between the skin chrominance information is also proposed. This enables skin modelling without concerning about the data correlation. We model the skin color pixels by applying the proposed distributions in five different color spaces. The Compaq dataset was used for evaluating the performance of the proposed method. The accuracy of skin detection on the Compaq data set was 88% and showed improvement compared to previous statistical methods.**

***Index Terms*—Skin Detection; Beta Distribution; Gamma Distribution; Laplace Function; Gaussian Distribution; Parametric Modelling.**

I. INTRODUCTION

Many machine vision applications related to humans require to identify the human skin region in arbitrary images as a preliminary step. Face detection [1], eye detection [2], objectionable image filtering [3], and hand gesture recognition [4] are among the applications that use skin detection as a preliminary step to find the region of interest for more sophisticated processing in later stages of their algorithms. Two main trends are available for detecting human skin: Pixel-based and Regional-based skin detection. Pixel-based methods rely on skin color model obtained from a set of skin pixel, and the skin model is used to determine if an input test pixel is a skin pixel or not [5]. Regional-based methods use the color and texture information of a subset of image pixels to determine the skin region in an image [6, 7]. Pixel-based skin detection presents a fast and easy way to implement skin detection system, but they are not as accurate as regional based methods. However, easy implementation and low computation overhead makes these methods attractive for many machine vision applications where computation complexity is of a significant matter [8].

Parametric skin detection is a conventional pixel-based skin detection strategy that uses statistics of sample skin pixels for skin detection. To implement the method, first a skin color histogram is built from a collection of sample skin pixels, and the histogram is used to calculate the Probability Distribution Function (PDF) of skin pixels with an appropriate mathematical function. Gaussian distribution is the most common model for skin color modelling when parametric models are used [9].

In this paper we propose the use of three statistical functions, Gamma, Beta, and the Laplace distributions for modelling skin color pixels. These functions present additional shape control parameters compared with the Gaussian distribution, which promises better skin detection accuracy. However, as opposed to the Gaussian distribution that inherently takes into account the data correlation, the proposed distributions do not consider data correlation. Hence, we present a transformation that enables modelling the skin PDF using the Gamma, Beta and Laplace distributions without requiring to consider data correlation. We test several color space for skin detection and use the COMPAQ skin dataset for training and test stages.

The rest of the paper is organized as follows: Section II reviews pixel-based skin detection methods. In Section III, the details of the proposed method is explained. Experimental results are shown in Section IV and Section V concludes the paper

II. RELATED WORK

Three steps for skin detecting skin pixels using color information have to be considered: (1) choosing an appropriate color space to represent image pixels, (2) model skin and non-skin pixels using a suitable distribution and (3) classification of the modelled distributions. We review some of the most frequent color spaces and distributions used for representing and modelling the skin color distribution in the following subsections.

A. Color spaces

Choosing an appropriate color space is the first step in detecting skin pixels. RGB is the default color space for many image formats. Other color spaces are derived from RGB space by linear or non-linear transforms. It has been shown that skin pixels vary more in intensity, so it is conventional to drop the luminance color and only use chromaticity information for skin detection [9].

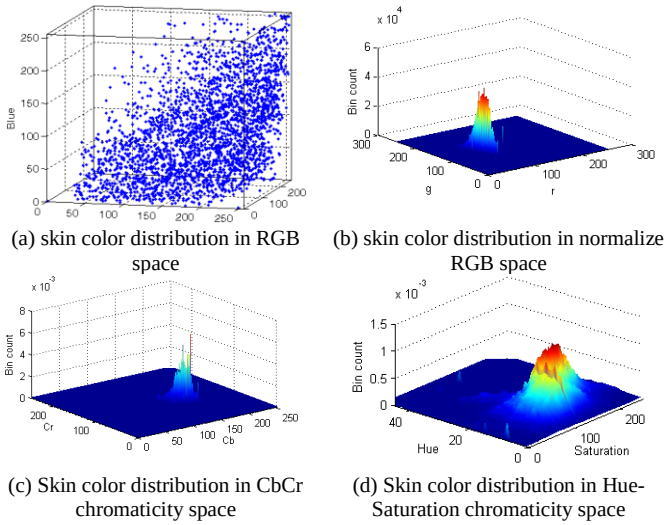
i. RGB and normalized RGB color spaces

RGB is the most frequent color space for storing digital images. High correlation between the color channels and mixing of luminance and chrominance information makes this

space inappropriate for image processing application. However, the fact that no color transformation is required, RGB space has been used for skin detection [10]. Figure 1(a) shows the distribution of skin pixels in the RGB color space. For better visualization, color quantization has been performed. As Figure 1(a) shows, skin pixels spread in a very large area of the RGB space; hence, it is not easy to cluster the skin pixels in a small area of the space. In order to neutralize the effect of luminance, a normalization on the RGB space can be performed as:

$$r = \frac{R}{R+G+B},\quad g = \frac{G}{R+G+B},\quad b = \frac{B}{R+G+B} \tag{1}$$

In this equation, R, G and B represent Red, Green and Blue channel of the RGB space. Since r + g + b = 1, two components hold the required information, and the third component becomes redundant. Since this representation holds less luminance information, and easily obtained from the RGB space, normalized RGB space has been vastly used for skin detection [11-13]. The distribution of skin pixels from the training set of images used in this paper is shown in Figure 1(b). As it can be seen, in this space, the skin color pixels cluster in a smaller are of the chromaticity plane, which is a desirable fact for skin detection.



(a) skin color distribution in RGB space

(b) skin color distribution in normalize RGB space

(c) Skin color distribution in CbCr chromaticity space

(d) Skin color distribution in Hue-Saturation chromaticity space

Figure 1: Skin color distribution in different color space. The histograms are obtained from the skin pixels in the training set used in this paper for skin detection.

ii. Orthogonal color spaces

Orthogonal color spaces reduce the redundancy of RGB color space and describe color as uncorrelated as possible. In these spaces, Luminance is described as a linear combination of the R, G, and B values. The other two components are the difference between the luminance value and the components of the RGB value. Such color spaces that have been frequently used for skin detection include: YUV [14, 15] and YCbCr space [3, 13]. YCbCr space being the most attractive orthogonal space for skin detection is calculated from the RGB space as [9]:

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ Cr &= R - Y \\ C_b &= B - Y \end{aligned} \tag{2}$$

Figure 1(c) shows the distribution of skin pixels in the Cb-Cr chrominance plane.

iii. Perceptual color space for skin detection

Perceptual color spaces are used to describe the color properties with numbers that are more understandable by the human mind [16]. These spaces are not linearly convertible from the RGB space, but many non-linear transformations have been made available for this purpose. One of the most widely used perceptual color spaces for skin detection is the HSV color space. Were H stands for Hue information, S shows the saturation, and V is for value. Transformation from RGB to HSV is obtained as in Equation 3, where *max=max(R,G,B)*. Skin pixel distribution in the Hue-saturation plane is shown in Figure 1(d). As shown in the figure, skin pixels scatter widely along the saturation axis. On the other hand, on the Hue axis skin pixels cluster in a small region. Robustness against illumination variations makes this color space attractive for skin detection [17].

$$H = \begin{cases} 0 & if\ \max = \min \\ \left(60^\circ \times \dfrac{G-B}{\max - \min}\right) \bmod 360^\circ & if\ \max = R \\ 60^\circ \times \dfrac{B-R}{\max - \min} + 120^\circ & if\ \max = G \\ 60^\circ \times \dfrac{R-G}{\max - \min} + 240^\circ & if\ \max = B \end{cases} \tag{3}$$

$$S = \begin{cases} 0 & if\ \max = 0 \\ 1 - \min/\max & otherwise \end{cases}$$

$$V = \max$$

iv. CIE-XYZ color space for skin detection

The CIE_1931 color spaces are the first defined quantitative links between physical pure colors (i.e. wavelengths) in the electromagnetic visible spectrum, and physiological perceived colors in human color vision. CIE-Lab and CIE-LUV color spaces are derived from the CIE-XYZ space which have been attractive for skin detection [18, 19]. Similar to the RGB space, it is desirable to normalize this space to reduce the correlation among the color channels of the XYZ space. XYZ space is obtained from the RGB space via the following equation:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \frac{1}{0.176} \begin{bmatrix} 0.49 & 0.31 & 0.20 \\ 0.17 & 0.81 & 0.01 \\ 0.00 & 0.01 & 0.99 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

B. Pixel-based skin detection

Explicit rule based skin detection, Bayes rule, and parametric skin detection are the conventional methods for

detecting skin pixels using pixel level information [20]. Explicit rule based skin detection is based on the idea that skin pixels cluster in a small region of an appropriate color space. It is possible to define rules applied to color components of one or multiple color components and use them to classify pixels as skin or non-skin. Although this method is easily implemented, low detection accuracy makes it unfavourable for skin detection, unless it is used to estimate a prior estimation of the skin region in an image. In [21], the HSV color space is used to find an initial estimate of the skin region. The rules are defined as: H ∈ [1, 50], and S ∈ [.6, 1], where Hue is scaled in the range of [0 359] and S is in the range of [0 1].

Bayes rule has also been used for skin detection extensively and can be defined as:

$$P(skin|c) = \frac{P(skin|c)P(skin)}{P(c|skin)P(skin) + P(c|-skin)p(-skin)} \quad (5)$$

where *P(-skin)* and *P(c|skin)* can be calculated as:

$$p = \frac{Skin[c]}{\sum skin} \quad (6)$$

where c is the color of a skin pixel. For each pixel if $P(c|skin) > T$ then, c is classified as skin [19]. T is a suitable threshold. Incompleteness of the samples representing the skin histogram might lead to unsatisfactory skin classification results. Hence, to reduce the effect of incomplete data, parametric models for skin detection have been proposed.

In order to model the skin color distribution in a desired color space, parametric skin detection methods have been introduced [10, 13]. Parametric methods resolve the shortcoming of the methods based on the Bayes rule by using a statistical model to present the skin color pixels distribution. The Gaussian distribution proposed by [10] calculates the skin probability of a pixel by the Gaussian distribution defined as:

$$P(c|skin) = \frac{1}{2\pi|\Sigma_s|^{1/2}} \times e^{-\frac{1}{2}(c-\mu_s)^T \Sigma_s^{-1}(c-\mu_c)} \quad (7)$$

where μ is a vector containing the mean value of skin color pixels in each color component, and ∑ is the covariance matrix. Figure 2 shows the skin color PDF in the nRGB color space using the Gaussian distribution function in two different views. The elliptic boundary model [13] and the Since [22] function have also been proposed for detecting skin pixels using parametric modelling of skin pixels.

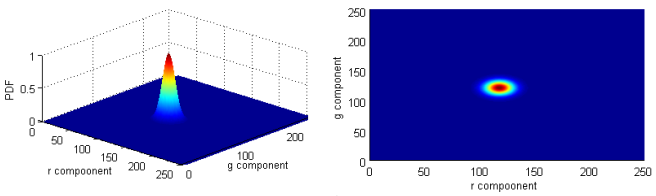


Figure 2: Skin color model obtained from the Gaussian distribution in two different views

III. Statistical Models for Skin Detection

Choosing a distribution function that tightly fits the skin color pixels is an essential step in the skin detection process. If more than one color component is chosen for representing skin color pixels which is the most common way to represent skin color, then any statistical distribution can be adapted for modelling skin color pixels. If the skin pixel data are no correlated, and the skin distribution in each color component is represented by $P_i(x)$, $i = 1,...N$ where N is the number of color component that represents skin pixels, the joint probability of P_i can be calculated as:

$$P(x) = \prod_{i=1}^{N} P_i(x) \quad (8)$$

In most cases, the color components are correlated and (8) will not be sufficient for modelling the skin color. When Gaussian distribution is used for skin detection, the covariance matrix required for calculating *P(c|skin)* inherently holds the correlation between data and is calculated as:

$$\Sigma = \begin{bmatrix} E_{11}[(X_1-\mu_1)(X_1-\mu_1)] & E_{12}[(X_1-\mu_1)(X_2-\mu_2)] \\ E_{21}[(X_2-\mu_2)(X_1-\mu_1)] & E_{22}[(X_2-\mu_2)(X_2-\mu_2)] \end{bmatrix} \quad (9)$$

where $E_{12} = E_{21}$ show the correlation between X_1 and X_2. If X_1 and X_2 are independent then $X_{12}=X_{21}=0$. The covariance matrix can be represented by eigenvalues and eigenvectors of its components as:

$$\Sigma = \sum_{i=1}^{D} \lambda_i u_i u_i^T \quad (10)$$

where D is the dimension of data, u is the eigenvector matrix, and λ is the eigenvalues vector. For $D \in R^2$, u is a 2×2 matrix where each column shows the direction for which data are distributed along it with the most and least variance. The eigenvectors of the data are perpendicular to each other. If the data are not correlated, the eigenvectors are further made parallel to the axis of the representative space; otherwise the eigenvectors are not parallel with the axis of the data space (Figure 3) [23].

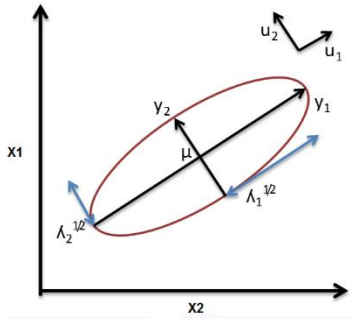


Figure 3: Eigenvector configuration for correlated data in 2Dspace.

In the Gaussian distribution, the covariance matrix is inherently considered in the calculation of the skin color

model. For the Beta, Gamma, and Laplace functions, we present a transformation so that in the covariance matrix, elements $E_{12} = E_{21} = 0$. This is equivalent to a rotation and linear translation of the data, so that the eigenvectors of the data are parallel to the chromaticity space axis.

The proposed transformation has two stages: First, the skin color cluster in any desired chromaticity space is transformed to the center of the space. Then, the covariance matrix of the data is calculated and the eigenvectors of the skin color cluster are obtained. Having the eigenvectors, it is possible to rotate the data so that the eigenvectors of the data are parallel to the chromaticity space axis. When this task is performed, it can be implied that the data are transformed in a way that there is no correlation between X_1 and X_2. Having such a cluster of data, any function can be used to build a 2D version of the distribution fitted to the skin pixels using (8). When the skin color model is obtained, it is possible to rotate the data and transform it back to its original point in the chromaticity plane. To formulate this process, the following steps were implemented: Two mesh grids were constructed as:

$$Grid(X1) = \begin{bmatrix} 1 & \cdots & 256 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 256 \end{bmatrix} - mean(X_1) \tag{11}$$

$$Grid(X_2) = \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 256 & \cdots & 256 \end{bmatrix} - mean(X_2) \tag{12}$$

and were shifted to the center of the chromaticity space. The covariance of the data is then calculated by:

$$Cov_H(X) = \begin{bmatrix} \sigma(Grid(X_1), H(X)) & Corr(Grid(X_1), Grid(X_2), H(X)) \\ Corr(Grid(X_1), Grid(X_2), H(X)) & \sigma(Grid(X_2), H(X)) \end{bmatrix} \tag{13}$$

where σ represents variance and *Corr* represents the correlation between the data. Upon calculation of the covariance matrix, it is possible to find the eigenvectors and eigenvalues of the covariance matrix which are shown as v_x and λ_x respectively. These values are calculated by solving the equation:

$$v_X X = \lambda_X X \tag{14}$$

$$\left| Cov_H(X) - \lambda I \right| = 0 \tag{15}$$

and the eigenvalues are substituted back into (14) to find the eigenvectors. The required transformation needed to make the eigenvectors parallel to the chromaticity axis is:

$$\begin{bmatrix} Grid_{new}(X_1) \\ Grid_{new}(X_2) \end{bmatrix} = v_X \times \begin{bmatrix} Grid(X_1) \\ Grid(X_2) \end{bmatrix} \tag{16}$$

By applying (16) the $Grid_{new}(X_1, X_2)$ now holds the data that are not correlated. This transformation on skin color pixels in the YCbCr space is shown in Figure 4.

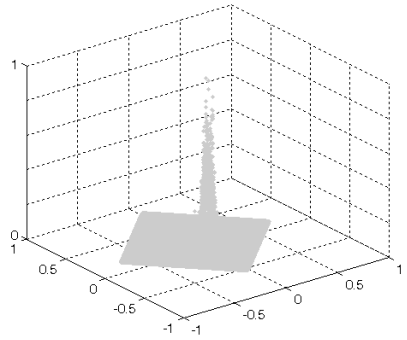


Figure 4: Un-correlated data in the YCbCr color space using the proposed transformation method.

Since data are uncorrelated under this transformation, (8) can now be used to calculate the joint probability of data without concerning about their correlation. Using the above transformation, the proposed skin detection method can be implemented in two phases: training and test phase. The training phase is conducted to obtain the skin color model by implementing the following steps:

1. Collect sample skin pixels.
2. Transform the skin color pixels to the desired color space.
3. Use the proposed transformation to Un-correlate data.
4. Calculate model parameters for each color component independently and use (8) to find their joint probability.
5. Transform the trained model to its original place in the chromaticity space.
6. Save the skin probability for each chromaticity value in a 256×256 Look Up Table (LUT).

In the test phase, each pixel c undergoes the following steps in order to be classified as skin or not:

1. Transform test pixel c into the desired color space.
2. Calculate $P(c|skin)$ using the stored skin probability LUT.
3. If $P(c|skin) > T$ classify pixel c as a skin, where T is an appropriate threshold value.

A. Gamma Distribution

Gamma distribution is a two-parameter family of probability distributions. This distribution has a scaling parameter θ and a shape parameter k. The gamma Probability Distribution Function (PDF) can be defined by $\theta > 0$ and $k > 0$ as:

$$gamma(x; k, \theta) = x^{k-1} \frac{e^{-x/\theta}}{\theta^k \Gamma(k)} \tag{17}$$

The model parameters k and θ can be calculated using the mean and variance of the training skin pixels, where $\mu = K\theta$ and $\sigma = k\theta^2$. Γ is the gamma function and is defined as $\Gamma(n) = (n-1)!$. Since (8) is used for modelling the joint probability of the skin color distribution, the final skin model using chromaticity information in a desired color space can be calculated as:

$$P(c \mid k_d, \theta_d) = \prod_{d=1}^{2} \left(x^{k_d - 1} \frac{e^{-x/\theta_d}}{\theta_d^{k_d} \Gamma(\theta_d)} \right) \tag{18}$$

where *d* is the dimension of the color components used for modelling skin PDF which equals to two in our study.
Figure 5 shows the skin color model obtained in four different color spaces. Figure 5(a) shows the skin color model in nRGB color space, Figure 5(b) shows the skin color model in YCbCr color space. In these two figures, the histogram of skin color pixels and $-1 \times gamma(c,k,\theta)$ are shown for better visualization. Figure 5(c) shows the skin color model in YCbCr chromaticity plane in a different view, and Figure 5(d) shows the skin color model in the XYZ chromaticity plane. Comparing Figure 5 with Figure 2, it is evident that Gamma distribution models skin color are more flexible compared with the Gaussian distribution function. It is expected that better skin detection result is obtained using the Gamma distribution.

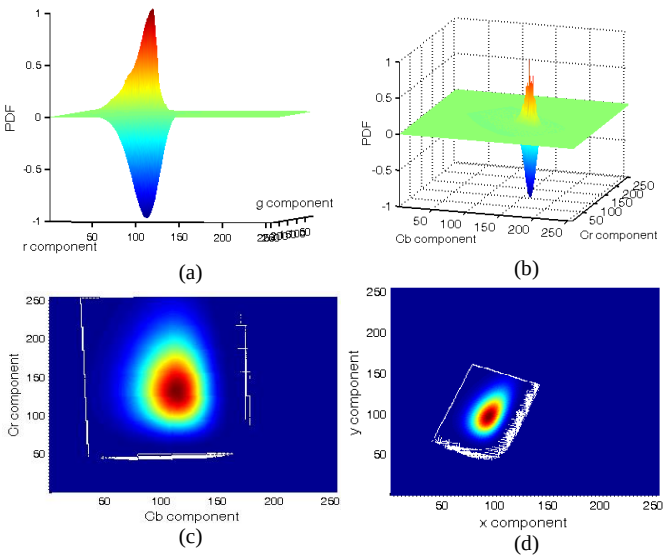


Figure 5: Skin model obtained using the gamma distribution in a) the nRGB color space, b) YCbCr, c) XYZ, and d) YUV color space.

B. Beta Distribution

In probability theory, the beta distribution is a continuous probability distribution which is parameterized with two shape parameters, *a* and *b*. Beta distribution is defined in the interval [0 1], and in order to be used for modelling skin pixels, data are required to be scaled in the interval [0 1]. This distribution has been useful for modelling the behaviour of random variables that have finite length. The beta PDF can be obtained via:

$$Beta(x \mid a,b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)} x^{a-1}(1-x)^{b-1} \tag{19}$$

The model parameters can be calculated from the first and second order statistics of the data where $\mu = a/(a+b)$ and $\sigma = ab/((a+b)2+(a+b+1))$. The Beta distribution that is used for modelling the skin color PDF in the chromaticity plane can be calculated as:

$$P(c \mid b_d, b_d) = \prod_{d=1}^{2} \left(\frac{\Gamma(a_d)\Gamma(b_d)}{\Gamma(a_d + b_d)} x^{a_d - 1}(1-x)^{b_d - 1} \right) \tag{20}$$

Figure 6 shows the skin color PDF obtained from the training skin pixels in nRGB and YCbCr chromaticity plane using the Beta distribution.

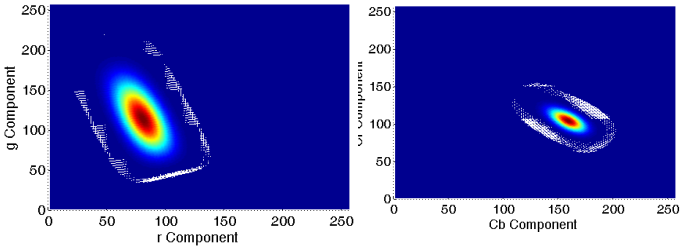


Figure 6: Skin color model in nRGB and YCbCr color space using the Beta distribution

C. Laplace Function

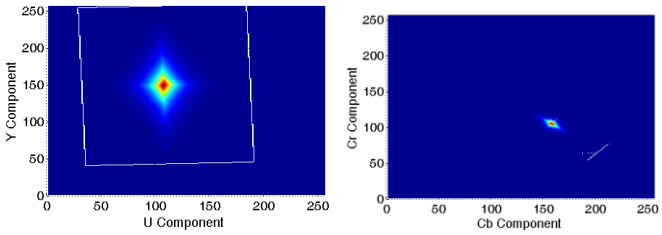
The Laplace function or the double exponential is a continuous statistical function that is made up of two back to back exponentials. Since the double exponential function can be described with two variance values on each side, this function can model the skin color model with more flexibility compared to the Gaussian distribution. The Laplacian function can be formulated as:

$$\begin{aligned} laplacian(x \mid \mu, b) &= \frac{1}{b} e^{\left(\frac{-.5|x-\mu|}{.5b \cdot 5} \right)} \\ &= \frac{1}{2b} \begin{cases} epx\left(-\frac{x-\mu}{b} \right) & if \ x < \mu \\ \exp\left(-\frac{\mu - x}{b} \right) & if \ x \geq \mu \end{cases} \end{aligned} \tag{21}$$

where μ is the mean value and $b>0$ is the scale parameter calculated as $b = 5.\sqrt{\sigma}$. The skin color model via the Laplace function and chromaticity information is obtained as:

$$P(c \mid \mu_d, b_d) = \prod_{d=1}^{2} \left(\frac{1}{\text{var}_d} e^{\left(\frac{-.5|c-\mu_d|}{.5b_d \cdot 5} \right)} \right) \tag{22}$$

The skin color model using the Laplacian function in YCbCr and YUV space is shown in Figure 7.



(a) (b)

Figure 7: Skin color model using the Laplacian function in a) YUV and b) YCbCr chromaticity planes.

IV. Experimental Results

This section reports the result of skin detection using the proposed distribution functions. The Compaq dataset introduced in [10], has been used for the training and test stages. The dataset contains over 6000 manually labelled skin images and over 8000 non-skin images. Divers lighting conditions and complex scenes make this data set suitable for evaluating our method for skin detection. From the set of skin images available in this dataset, 2000 image were used to build the skin color histograms. 4000 skin and 4000 non-skin images were used for testing the proposed method. Some samples from this dataset is shown in the Appendix. Five different color spaces were chosen for skin detection: nRGB, YCbCr, HSV, YUV, and XYZ. Examples of the skin models obtained for each color space were shown in various figures of the previous section. In order to compare our method with the other pixel based skin detection methods, we chose the Gaussian distribution [10] which is the baseline distribution for pixel based skin detection, and the Sinc function [22]. The Elliptic model [13] has been previously tested against the Sinc function and the Gaussian distribution in [22] by utilizing the Compaq dataset. For quantitative analysis of the results, Receiver Operating Curves (ROC) were used and shown by True Positive Rate (TPR) and False Positive Rate (FPR). TPR is defined as:

$$TPR = \frac{True\,Positive}{True\,Positive + False\,Positive} \quad (23)$$

$$FPR = \frac{False\,Positive}{True\,Positive + False\,Positive} \quad (24)$$

Figure 8 shows the ROC curves of skin detection in nRGB chromaticity space were the color channels r and g were used for skin color representation. As the curves show, the skin detection results are not significant as the ROC curves deviate from the vertical axis as TPR approaches 100 percent. However, the Gamma distribution shows to be the better distribution for modelling skin color in nRGB color space. The Beta and Laplacian distributions did not show good results for modelling skin color pixels in the nRGB color space.

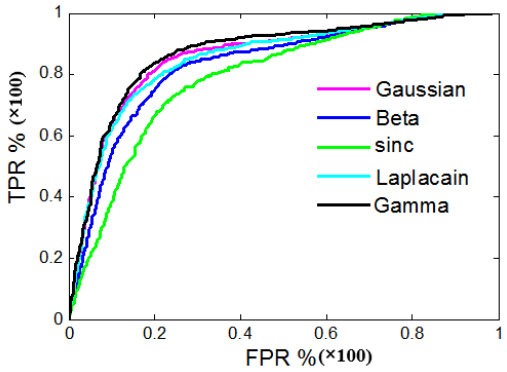


Figure 8: ROC curves for skin detection in nRGB color space

Figure 9 shows the skin color detection results in the YCbCr space. Comparing the ROC curves obtained in this color space, with nRGB space, it shows that YCbCr space is a good color space compared to the nRGB space. Skin color models nearly show the same results for skin detection in this color space. However, the ROC curves obtained for the Gamma function show that this model results in more accurate skin detection.

Figure 10 shows the result of skin detection in YUV color space. The ROC curves in this space show when Beta distribution and Laplacian functions were used for skin detection, better results were obtained. The Sinc and Gamma function showed very poor results in this color space. For skin detection using the Gaussian distribution in YUV color space, the obtained ROC curve was closely the same as the ROC curves for Beta and Laplace distributions.

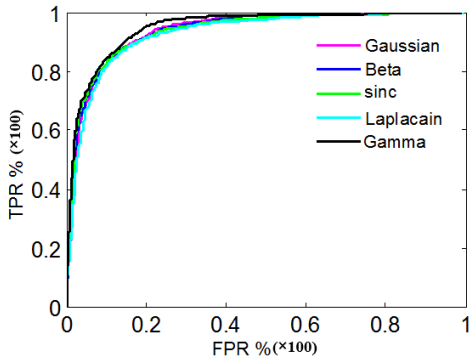


Figure 9: ROC curves for skin detection in YCbCr color space.

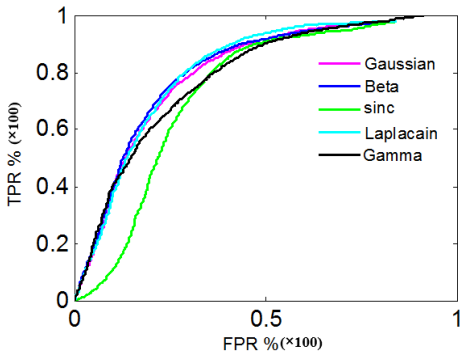


Figure 10: ROC curves for skin detection in YUV color space.

Figure 11 shows the result of skin detection in HSV color space. The ROC curves obtained for skin detection in the HSV color space show that H and S color components are not desirable spaces for skin detection. This is an expected result as Figure 1(d) shows that skin pixels scatter widely along the saturation axis. Hence, this color component does not yield good results for skin detection. However, the Hue component has shown to be effective for skin detection when used individually for fast estimation of skin pixels [3]. The ROC curves for skin detection in XYZ color space show that all the distributions used for modelling the skin color pixels are closely the same expect for the Sinc function (Figure 12). In order to observe the result of skin detection quantitatively, Table 1 shows some results of skin detection obtained from

the ROC curves of Figure 8 to 12. For each color model, in each color space, the FPR values for TPR = 90% and TPR = 100% are shown in the table. As the FPR values show, the YCbCr space is the better color space for skin detection on the tested dataset. For TPR = 95% only 14.48% FPR was achieved, which was at least 3% better than FPR values when compared to other skin models. In other color space, the FPR values were over 30% which shows that YCbCr is more suitable color space for skin detection.

Among the three models presented in this paper, the Gamma distribution showed to be the most efficient distribution for modelling the skin color pixels.

Table 1
The Results of Skin Detection using the Proposed Statistical Models.

		Gamma	Beta	Laplacian	Gaussian [10]	Elliptic [13]	Sinc [22]
YCbCr	90	14.38	17.38	17.88	17.40	44.3	17.56
	95	15.80	25.92	31.88	30.66	58.3	28.10
nRGB	90	30.00	38.70	41.24	39.16	43.2	56.28
	95	63.25	69.66	66.22	67.24	58.3	69.00
YUV	90	49.60	43.86	41.16	45.22	-	47.62
	95	64.62	63.26	54.22	60.96	-	73.00
HSV	90	37.12	27.07	28.52	28.36	-	27.02
	95	46.12	38.40	39.10	39.06	-	41.98
XYZ	90	31.26	23.00	37.26	27.90	-	51.86
	95	42.90	43.00	58.34	51.32	-	62.26

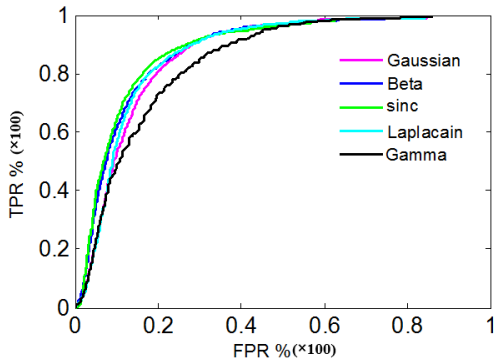


Figure 11: ROC curves for skin detection in HSV color space

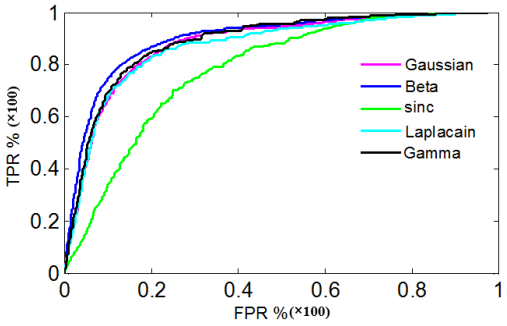


Figure 12: ROC curves for skin detection in XYZ color space.

V. Conclusions

This paper proposed applying Gamma, Beta, and Laplace distributions for human skin detection. A new method for eliminating the correlation between the chromaticity values of image pixels was also presented, which was required to obtain the skin color models efficiently. To implement the method, first the skin color, histograms were transferred to the origin of the chromaticity plane and were rotated so that eigenvectors of the skin data were parallel to the chromaticity axis. The application of this step resulted into zero cross-correlation between the sample skin pixels. After this transformation, a one dimensional skin model using the desired statistical distribution was trained for each chromaticity component. The resulting one dimensional color models were multiplied to obtain the final 2 dimensional skin color model. The results of skin detection in 5 different color spaces showed that the proposed statistical models for skin detection outperformed the Gaussian distribution. Further, the results revealed that when Gamma function was used for skin detection in the YCbCr space, the result of skin detection improved by 3% compared to other methods tested in this paper. Higher accuracy of the proposed method for skin detection makes it attractive and applicable for applications that require human skin detection.

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APPENDIX:

Samples from the Compaq skin dataset. The dataset can be made available at the request from the Authors of [10].

Skin samples

Non-skin samples