Superior Skin Color Model using Multiple of Gaussian Mixture Model

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Abstract

Skin color based segmentation has been used intensively for locating and extracting the regions of human skin in an input scene, this skin color needs accurate modeling for better performance, color cue is the main information that can be used in pixel based methods that classified each input pixels to be either skin or non-skin pixel separately, Gaussian Mixture Model (GMM) has been used for that purpose to model the skin color pigment by the help of a selected color model, each color model has several shortcomings during its operation and the overall segmentation accuracy can be enhanced in case of several color models are mixed within one superior model, in this paper, we have presenting a new superior model for pixel based skin color segmentation using multiple of GMM in which each one tones a separate color model to overcome the emerging shortcomings that may occur by adopting a single color model and combining multiple color models in a single superior one, we have calculated three metric parameters to evaluate the accuracy of our proposed method compared with a single GMM for each adopted color model and we have achieved good and promising results, some experiments have done using indoors and outdoors images after training operation are also included.

Keywords: Skin Color, Segmentation, Gaussian Mixture Model, GMM, normalized RGB, HSV, YCbCr.

Introduction

The main idea of pixel based skin color segmentation is to locate and extract the pigment of the human skin in an input image that may contain complex scene as well as different objects because all the segmentation methods assume that the skin color can be differentiated from the background color or other object's colors that may exist in the input scene and a human skin cluster in specific color model can be formed [1] to achieve this purpose, human skin is a good indicator for the human presence [2] and can help to reduce the search space for face and hand to be within extracted regions instead of searching the whole image [3] and pixel based skin color segmentation can be done with fast computations whatever the pose is [3].

Good segmentation is the one that can identify the different ethnic groups like (blackish, brownish, whitish, etc.) and overcome the changes that caused by different lighting conditions [3] as well.

Many algorithms have been introduced in this area like Gaussian classifier, histogram with lookup table, Bayesian classifiers than can be used with Gaussian or histogram as well with the help of expectation-maximization or maximum likelihood estimation for adjusting and obtaining better fitted parameters for corresponding algorithm for better skin modeling and extraction.

Related Work

The main purpose of segmentation operation is to locate a specific object end proper extraction, this object can by a human skin color or any other object that may take any shape, color modeling and shape modeling are considered the main techniques for extraction which based on color features and compactness information respectively, for skin color based segmentation the location of the hand is required at the processing by many algorithms [4] to make the segmentation process more simple, furthermore, gray level thresholding technique was adopted in [5][6][7] for skin area extraction but this technique is unreliable for complex scenes, more robust segmentation algorithm in this field is color space based skin filter which locates the pigment of the human skin, moreover; many researchers claim that the chromaticity of the human skin is mostly similar across different ethnic groups [8][9], by adopting this idea; the luminance of the input pixel can be ignored accordingly and the chrominance can be used adopted for human skin extraction, different of color models have been applied for that reason by neglecting the lighting parameter, YCbCr is applied in [8][10][11][12] by modeling CbCr for skin color based segmentation, LUV has been used in [13] by neglecting V component, HSV has been used in [14][15] by ignoring V component, YUV has been used in [16] by removing Y component. Table 1 highlights some techniques in this direction, however, these color space based techniques are unreliable to lighting variance [14] and light intensity can mislead the segmentation process; however, the lighting reflection and color pigment outcome under different lighting condition can be modeled for proper segmentation process [10].

Color Distributions Taxonomy

In order to extract the skin color we need to find the distribution of that skin color at first step to be our reference for any skin color encountered as testing step, this distribution can be one of the following two distributions [1]:

Generic Color Distribution

Fixed range that corresponds to specific color model is used here to classify the skin pixels and non-sin pixels [1], this range is derived normally from the training data and as seen it is simple and fast and can be used for real time applications [1], but on the other hand, this model is limited and affected by change in lighting conditions as well as human skin color [1], thresholding techniques are good example.

Statistical Color Distribution

In this case, the human skin for different of ethnics groups can be modeled in the system with the ability of recovering the change in light conditions, this can be divided further into:

(a) Parametric

This kind of color distribution classifies the input pixels according to predefined and pre-trained statistical model, the constructed model should approximate and fit the trained data [27], these training data is represented by a parametric functional form that can be unimodal Gaussian or mixture of Gaussian [3] depends on the class(s) that might emerged from the skin color distribution [1] and application used, example is GMM.

(b) Non-Parametric

The probabilities of given color values is estimated based on trained data without any explicit color model [27] for fitting these data, histogram can represent an example for such technique in which the Bayes classifier [27] is used for classification of skin and non-skin pixels depending on the estimated probability.

Figure 1 shows a portray view of the above taxonomy.

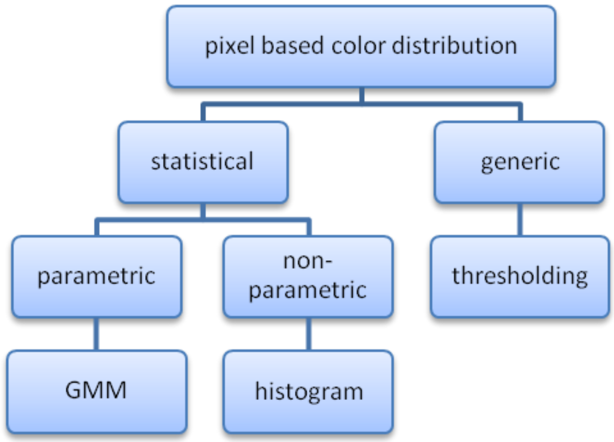


Figure 1: Color distribution taxonomy regarding pixel based skin color segmentation.

Operation Steps

The main steps for pixel based skin color segmentation can be totalized to three steps [2]:

Selecting Color Model:

The targeted color model should be chosen that reflects the kind of the applications, mostly, the original color model is RGB color model since it is used as a color palette for these images or videos, this RGB should converted to one of the available chose color models for further processing.

Selecting Color Model Parameters:

The parameters of the selected color models should be selected in which the skin color will be represented by these parameters only, usually the illumination parameter is dropped to provide robust algorithm against different ethnic groups and obtaining 2D model with two parameters only.

Modeling:

Modeling the distribution of the skin color for classification purposes, this distribution should cover all the skin area in order to get better skin segmentation.

Color Model

Plenty of color models are used in this area, many researchers have used different color models, comparative studies for measuring the performance of the color models regarding the pixel based skin color segmentation have been adopted in [3][2][28] and [29].

HSI has been provide as the highest performance model for skin color segmentation in [2], however, for a low brightness points the output of HSI model is discontinuous [27], in other hand, YCbCr suffers from the false segmentation for the resembled skin region [22] and hence some remedy should be applied, YCbCr with Euclidian distance between the CbCr components is adopted in [8], KL transform is accompanying the implantation of GMM model of YCbCr [22], furthermore, some researchers choose to adopt this color model with GMM which depends on the type of images that they employed as in [12].

Gaussian Mixture Model

Is a collections of a finite number of Gaussian distributions, those models are used to fit a given data in which those data is classified into a classes and each class needs single Gaussian for fitting, the parameters of Gaussian need to be trained and this done normally with the iteration algorithm called Expectation-Maximization that provides an estimation, on the contrary, Maximum Likelihood Estimation technique difficult to find the model that estimates these parameters or sometimes this model is not found. In order to build a mixture model we need to fit each class of the given classed, each class can be modeled by using one of the following Gaussian pdfs.

Bimodal Gaussian Distribution

In this case a single random variable x has to be modeled and the data is 1D data, each class of data has single peak representing its distribution and the mixture is a collection of unimodal Gaussian pdf, Equation 1 shows the unimodal and Equation 2 shows the bimodal mixture model (BGMM), in these models $x \sim N(\mu, \sigma^2)$, μ is the mean value and σ is the standard derivation of given data class.

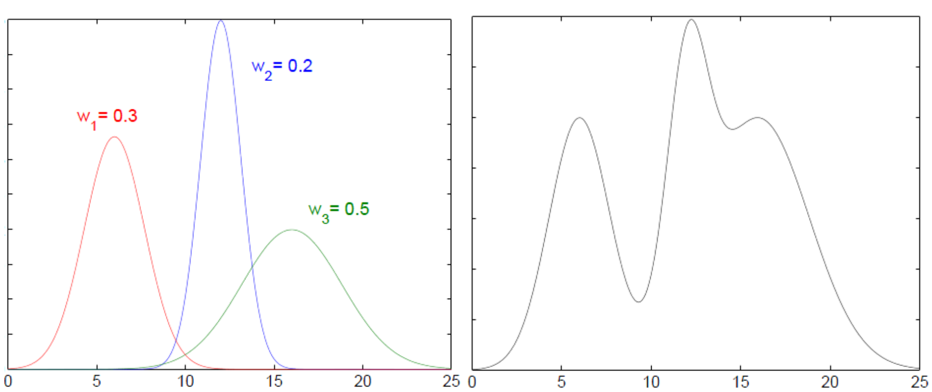
$$p(x;\ \mu,\sigma^2) = \frac{1}{\sqrt{2\mu}\sigma}\exp(-\frac{1}{2\sigma^2}(x-\mu)^2) \tag{1}$$

$$g(x) = \sum_{k=1}^{K} w_k\, p(x;\ \mu_k, {\sigma^2}_k) \tag{2}$$

Where K is the number of mixtures, w_k is the weight of component k of the mixture, and $g(x)$ is the mixture probability of x variable, furthermore, w_k should satisfy the following condition in Equation 3.

$$\sum_{k=1}^{K} w_k = 1 \quad and\ 1 \geq w_k \geq 0 \tag{3}$$

Figure (2) shows an example for such model.



A B

A: three models each is single Gaussian. B: bimodal mixture model corresponds to (A).
Figure 2: Bimodal Gaussian Mixture Model (from [30]).

Multivariate Model

In this case which is mostly used since most modeled data has higher dimension that 1D, however, in this model $x \sim N(\mu, \Sigma)$, the parameters x, μ are the same in bimodal except they are d dimensional space, i.e. $x = \{x_1, x_2, \dots, x_d\}$, and $\mu = \{\mu_1, \mu_2, \dots, \mu_d\}$ is the mean value for each space respectively, and $\sum$ is the covariance matrix, Equation 4 is the multivariate Gaussian distribution function, Equation 5 is the mixture of Gaussian for multivariate (GMM), Equation 6 is the $\sum$ matrix.

$$p(x;\ \mu, \Sigma) = \frac{1}{(2\mu)^{d/2}|\Sigma|^{1/2}} exp(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)) \qquad (4)$$

$$g(x) = \sum_{k=1}^{K} w_k\, p(x;\ \mu_k, \Sigma_k) \qquad (5)$$

$$\Sigma = \begin{bmatrix} \Sigma_{x_1,x_1} & \Sigma_{x_1,x_2} & \cdots & \Sigma_{x_1,x_d} \\ \Sigma_{x_2,x_1} & \Sigma_{x_2,x_2} & \cdots & \Sigma_{x_2,x_d} \\ & & \vdots & \\ \Sigma_{x_d,x_1} & \Sigma_{x_d,x_2} & \cdots & \Sigma_{x_d,x_d} \end{bmatrix} \qquad (6)$$

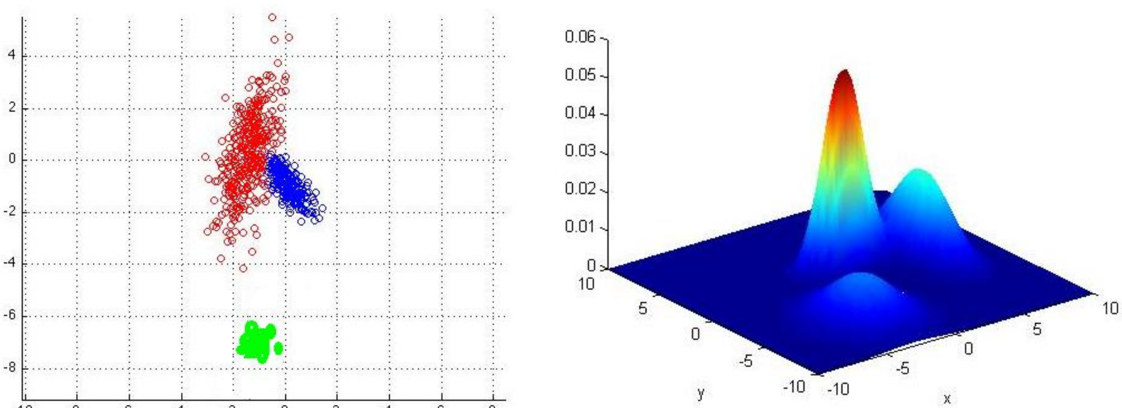
Where:

$$\Sigma_{XY} = E[XY] - E[X] * E[Y]\ , \forall\ \ X, Y\ \in d \qquad (7)$$

And:

$$E[X] = \sum_{i=0}^{n} \frac{x_i}{n} \qquad (8)$$

Figure 3 explains portray this model.



A B

A: three clusters of data (from [31]). B: multivariate Gaussian modeling (from [32]).
Figure 3: Gaussian Mixture Model example for 2D plane.

GMM also can model emission pdfs in HMM and the EM algorithm can estimate the parameters for emissions as well as for transition matrix and prior probabilities [30].

This model has been used for pixel based skin color segmentation, this model works under the premise we can found a single or mixture models for skin color distribution, but this is not always true [1] due to some influences that may arise, one more disadvantage is that the size of training data is large for covering different human skin [1], Table 2 shows an examples for number of training pixels for GMM, furthermore, experiment has been done by [33] for labeling the geometric shapes of different colors in an input image; three experiments have been done, 4, 3 and 10 mixtures have been adopted in each of first, second and third experiment respectively using RGB color space.

Proposed Technique

Each color model has some shortcoming for being adapted alone as aforementioned, we have suggested to combine several color models for achieving the correct segmentation and provide a superior fitted model that can get benefits from the adopted color models, we have used GMM for each single color model but these GMMs will be combined as well to form one superior model called Multiple of GMM (MuGMM), the new proposed model has proved its robustness comparing with using single color model as we will see in the forthcoming sections.

MuGMM: Preliminaries

We have combined three different color models for skin color modeling to form MuGMM, these color models are normalizedRGB, HSV and YCbCr, the reason behind using these models is their popularity for skin color segmentation as adopted by many researchers.

The skin color pigment is extracted and the distribution is calculated and modeled accordingly, the training is done using 757883 skin pixels, also we have trained the background color distribution using the same aforementioned models to make a good and fair comparative study about the existence of background color model or not, however, we have trained the background color distribution models with 341924 color pixels.

Mathematical Model

The mathematical model in this case can be seen as in Equation 9.

$$P(c|skin) = \max_{m \in M} g(c;\ \mu_m, \Sigma_m) \tag{9}$$

Where M is the number of color models employed, (μ_m, Σ_m) are the parameters associated with color model m necessary for single GMM modeling, and $g(c; \mu_m, \Sigma_m)$ is GMM defined in Equation 5 previously, and $P(c|skin)$ is the probability of color c being a skin color.

The probability of color c being non-skin color which is written as $P(c|\neg skin)$ can be modeled the same as Equation 9 but the corresponding parameters should be adopted, however, in order to decide whether this color c is a skin color or none; a threshold should be decided, we have adopted a Bayesian decision rule for finalizing this decision as Equation 10.

$$\frac{P(c|skin)}{P(c|\neg\ skin)} > \xi \tag{10}$$

Where ξ is a threshold which is normally has the value of one and the color c is belonging to skin class if this holds, however, this latter parameter can be adjusted in case of the background has not been modeled by assuming that the $P(c|skin) = P(c|\neg skin)$, furthermore, Bayes' rule can be adopted as well for determining the probability of current skin color c belongs to skin class as shown in Equation 11.

$$P(skin|c) = \frac{P(c|skin)}{P(c|skin) + P(c|\neg skin)} \tag{11}$$

And similarity, Equation 12 used to determine the probability of current color c belongs to non-skin class.

$$P(\neg skin|c) = \frac{P(c|\neg skin)}{P(c|skin) + P(c|\neg skin)} \tag{12}$$

Color Distribution

We have extracted the distribution of each adopted color model, the distributions' parameters have been listed in Table 3, these distributions have been extracted from the training pixels as we mentioned previously.

As seen in latter table, we have applied different number of mixtures for each color model depending on the distribution of the skin color in that model and to ensure the resulted model covers the entire skin color distribution.

Performance Evaluation

We have applied three metrics as in [1] have been adopted in this study of 100 images with their ground truth pictures for unifying the reference, as follows [1]:

Correct Detection Rate (CDR)

The percentage of the pixels that are classified correctly by the algorithm as skin pixels.

False Detection Rate (FDR)

The percentage of the pixels that are classified wrongly by the algorithm as non-skin pixels.

Classification Rate (CR)

The number of classified skin pixels correctly by the algorithm and ground truth divided by whichever maximum of each of number of skin pixels classified by the algorithm and number of skin pixels classified by the ground truth.

Mathematically speaking, Equations 13, 14, and 15 correspond to each of CDR, FDR, and CR respectively.

$$\mathrm{CDR} = \frac{C_s^a}{T_s^g} * 100\% \tag{13}$$

$$\mathrm{FDR} = \frac{W_{ns}^a}{T_{ns}^g} * 100\% \tag{14}$$

$$\mathrm{CR} = \frac{C_s^a}{\max\,(T_s^a, T_s^g)} * 100\% \tag{15}$$

Where C_s^a is the total number of pixels that correctly classified as skin pixels by the algorithm, T_s^g is the total number of pixels that classified as skin pixel by the ground truth, W_{ns}^a is the total number of pixels that are classified wrongly as non-skin pixels by the algorithm, T_{ns}^g is the total number of pixels that are classified as non-skin pixels by the ground truth, and finally, T_s^a is the total number of pixels that classified as skin pixel by the algorithm, Table 4 shows the different values of these parameters.

As seen by latter table, the best CDR achieved is in MuGMM which means the number of classified correctly as skin pixels is high in this algorithm, but, however, the FDR is higher than other models which means the area outside the hand object will have more added noise than other models, as a remedy for this noise, any noise removing algorithm can be applied to enhance this metric parameter, and regarding the last metric parameter CR, it is value is very close GMM using normalizedRGB, however, the overall performance can be seen by averaging of these parameters and the MuGMM has the high score, regarding FDR metric parameter, his best as his lower value, so must has the same interpretation when averaging with other parameters by deducting its value from 100% to reverse the interpretation and his performance will enhanced by high value gained, Figure 4 shows the pictorial representation of the final average of shaded cells in latter table.

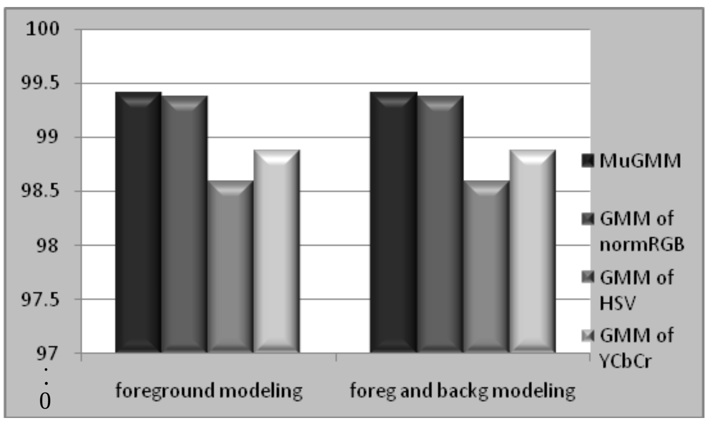
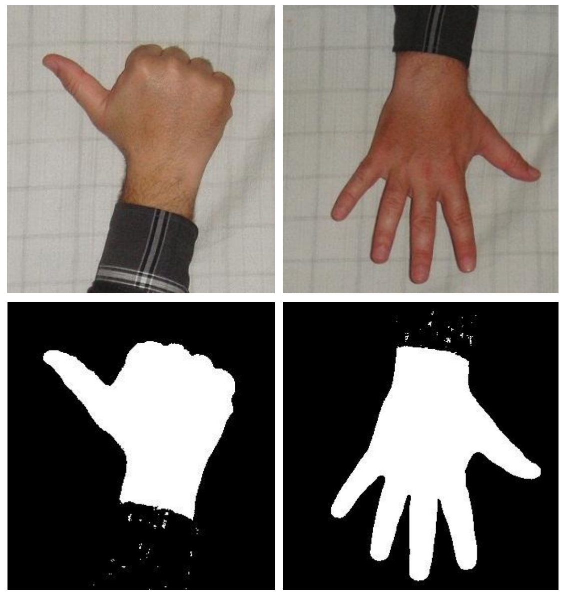


Figure 4: The average of matric parameters applied in Table 3.

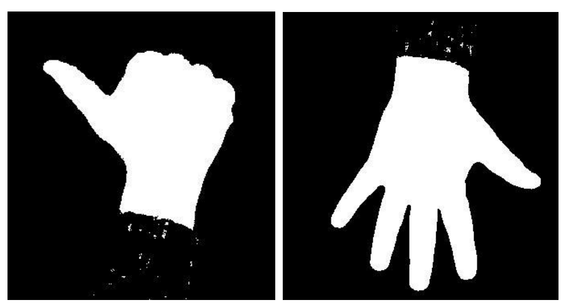
Experimental Results

We have applied 100 images as we mentioned for testing process, we have included in this section some images with skin color and some images with natural scenes, Figure 5 shows the segmentation process using our proposed algorithm in case of the training is applied for foreground regions only, Figure 6 shows the same but the training is done for foreground and background and the segmentation process are carried out accordingly.



A B
C D

A, B: original input images for testing.
C, D: skin color classification using MuGMM model corresponds to A and B respectively.
Figure 5: MuGMM segmentation using foreground training (skin color training).



A B

A, B: skin color classification using MuGMM model corresponds to Figure 5 (A and B) respectively.
Figure 6: MuGMM segmentation using foreground and background training.

We have applied the testing also on natural images with no hand object and the segmented images should be empty images as seen by Figure 7.

Conclusion

The skin color is the main cue for achieving a successful skin color based algorithm, this skin color should be modeled and fitted within the adopted model for proper results, the most important parameters can be modeled for that reason but this does not means the other parameters are not useful but they can be set to fixed value to simplify the modeling operation, the lighting components of the color models can be ignored but the performance of the proposed constructed algorithm using this color model will hesitate under lighting changing condition since this parameter is not modeled, however, for perfect modeling the lighting changing as well as the lighting reflecting from the surfaces should be included as well to achieve a robust algorithm that can work under different lighting as well as ethnic variations.

We have proposed a segmentation superior model that used the benefits of several color model as well as overcome their shortcomings, this model is based on modeling the skin color distribution using single GMM for each color model all adopted color models are unified using one superior color model, this model proved its robustness as compared with other color models as shows hereinabove.

A B C
D E F

A, B, C: original tested images with complex background.
D, E, F: skin color segmentation using MuGMM corresponds to A, B, and C respectively.
Figure7: Natural images with complex background for skin color segmentation test.

Future Work

Our future work is to construct this superior color model but this time by construction a superior mixture model which is called Mixture of GMM (MiGMM), in this case, we have applied a mixture of GMM instead of multiple of GMM, the mixture should be applied by calculating the weights of each adopted component of the mixture equation, the final model of MiGMM can provide promising classification results comparing with the MuGMM, the mathematical model are as shown in Equation 16.

$$P(c|skin) = \sum_{m=1}^{M} W_m\, g(c;\ \mu_m, \Sigma_m) \qquad (16)$$

Where c, M, m and $g(c;\ \mu_m, \Sigma_m)$ are the same interpretation as in Equation 9, and W_m is the weight of the component m.

Now, we need to find the value of the W_m which is the missing value in the suggested MiGMM model, this value can be found by calculating the classification rate as in Equation 15 since this parameter summarizes the classification rate of the algorithm, this metric parameter is calculated as seen in Equation 17.

$$W_m = \frac{CR_m}{\sum_{i=1}^{M} CR_i}, \forall\, m = 1, 2, 3, \dots, M \qquad (17)$$

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Table 1: Different segmentation techniques adopted by different researchers.

Method	Background	Segmentation Employed
[4]	Almost uniform	Gaussian modeling for background subtraction with shadow removing
[5]	uniform	thresholding
[6]	black	thresholding
[7]	n/a	thresholding the closest object to camera
[8]	uniform	color based YCbCr
[10]	almost uniform	color based YCbCr
[11]	fixed colors	GMM for background subtraction, color based USC for hand detection
[12]	Cluttered	GMM using YCbCr for foreground modeling, and background modelling
[13]	cluttered	color bases LUV
[14]	cluttered	statistical Gaussian model using HSV
[15]	almost cluttered	color based HSV
[16]	almost uniform	color based YUV
[17]	cluttered	infrared camera with thresholding
[18]	cluttered	background subtraction with reference image
[19]	cluttered	background subtraction with reference image
[20]	uniform	background subtraction with reference image
[21]	Cluttered	Hybrid, anding between GMM and histogram using rg and HSI respectively
[22]	Cluttered	Hybrid, anding between the KL transform and single Gaussian Distribution
[23]	Cluttered	GMM using YCbCr modeling
[24]	Almost uniform	H component only of HSV color space for extracting predefined coloured gloved
[25]	Black	HSI color space to extract the fingertips of predefined coloured glove
[26]	Cluttered	H component of HSV color space

Table 2: GMM modeling for skin based segmentation.

Method	Color space	Total Trained Image Pixels	Skin pixels	Number of mixtures for skin	Non-skin pixels	Number of mixtures for non-skin
[23]	YCbCr	107,292	18,972	4	88,320	1
[27]	YCbCr	-	127,352,563	7	-	-
[29]	Comparative study on normalized RGB and HSV	-	56,279	-	-	-
[34]	HSV	782,400	-	5	-	-

Table 3: Extracted parameters for modeling the skin color.

Color model	Modeled components	Mixture number	μ^T vector	$\sum$ matrix
Normalized RGB	r, g	1	(245, 143)	$\begin{bmatrix} 815 & -283 \\ -283 & 201 \end{bmatrix}$
		2	(302, 120)	$\begin{bmatrix} 314 & -109 \\ -109 & 92 \end{bmatrix}$
		3	(379, 86)	$\begin{bmatrix} 1228 & -739 \\ -739 & 509 \end{bmatrix}$
HSV	H, S	1	(14, 27)	$\begin{bmatrix} 96 & 5 \\ 5 & 57 \end{bmatrix}$
		2	(5, 28)	$\begin{bmatrix} 34 & 15 \\ 15 & 51 \end{bmatrix}$
		3	(22, 27)	$\begin{bmatrix} 30 & 1 \\ 1 & 41 \end{bmatrix}$
YCbCr	Cb, Cr	1	(-16, 27)	$\begin{bmatrix} 36 & -19 \\ -19 & 71 \end{bmatrix}$
		2	(-20, 32)	$\begin{bmatrix} 26 & 5 \\ 5 & 53 \end{bmatrix}$

Table 4: Calculating the metric parameters for accuracy of skin color segmentation.
Note: F denotes for Foreground modeling only, FB denotes for modeling of both foreground and background.

Parameter	MuGMM		GMM of normalizedRGB		GMM of HSV		GMM of YCbCr	
	F (%)	FB (%)	F (%)	FB (%)	F (%)	FB (%)	F (%)	FB (%)
CDR	99.873	99.873	99.652	99.65	97.937	97.937	98.402	98.402
FDR	0.474	0.474	0.441	0.441	0.115	0.115	0.188	0.188
CR	98.825	98.825	98.903	98.903	97.937	97.937	98.402	98.402
Average	99.408	99.408	99.371	99.371	98.586	98.586	98.871	98.871