CHAPTER V
DEVELOPMENT OF AUTOMATIC HUMAN SKIN DETECTION
TECHNIQUES WITH APPLICATION TO HUMAN FACE DETECTION

This Chapter mainly deals with a family of automatic human skin detection techniques with application to human face detection which overcome most of the limitations identified in the previous Chapter IV, which deals with the Comparative Analysis of the Automatic Human Skin Detection Techniques in Color Images and their Applications to Face Detection. The development of algorithms includes automatic human skin detection and face detection techniques.

The Comparative Analysis of research on Automatic Human Skin Detection techniques have yielded three major categories of areas, namely:

a) Explicitly-defined Skin Region Techniques
b) Parametric (Gaussian models) Techniques
c) Non-parametric (Bayesian models) Approaches.

Under the categories of above three skin detection approaches, algorithms are designed for the problems identified during the study and analysis of automatic human skin detection techniques applicable to face detection in color images.

a) Explicitly-defined Skin Region Techniques

In conventional explicitly-defined skin region techniques, the human skin is detected without using much computational work [65]. During literature survey, it is inferred that the explicitly-defined skin cluster techniques employeds a fixed threshold values, the images have different lighting conditions, background clutter is present in the image, multiple faces are located in the image, and variations in face position, scale, pose and expression are identified. The fixed threshold values do not produce good results.
To overcome these problems three algorithms are developed during the course of this work, namely FDTM: Human Face Detection in Color Images using Skin Color and Template Matching Models for Multimedia on the Web [85], FDPS: Face Detection in Color Images using Pixel Based Skin Color Detection Techniques [83] and FDMP: Skin-Color Based Human Face Detection using Mixed Piece-wise Linear Decision Boundary and Template Matching Classifier [127], which are found to be very efficient skin detection techniques and have reduced much of the computational work in finding the skin regions using the combination of commonly use color spaces like HSV, YCbCr and YIQ.

1. In conventional explicitly defined skin cluster methods, the threshold values used to segment the skin region are fixed values which cannot be used for all kinds of skin colors. Therefore, the threshold values are taken from the mean and standard deviation of skin pixels. To overcome these problems, a novel explicitly defined skin cluster technique is developed. By deploying these concepts in this research work, two algorithms, namely FDTM: Human Face Detection in Color Images using Skin Color and Template Matching Models for Multimedia on the Web and FDPS: Face Detection in Color Images using Pixel Based Skin Color Detection Techniques were developed.

2. The detection of skin regions in color images with single color space using explicitly-defined skin cluster methods applied to different types of color face databases produce false positives because the fixed threshold values cannot be used for all types of skin colors. Hence, the threshold values are taken from more than one color space [85]. To overcome these problems, a new explicitly defined skin cluster technique is developed. By deploying these concepts in this research work two algorithms, namely FDPS: Face Detection in Color Images using Pixel Based Skin Color Detection
Techniques and FDMP: Skin-Color Based Human Face Detection using Mixed Piece-wise Linear Decision Boundary and Template Matching Classifier are developed.

3. Individual color spaces behave differently for human skin detection techniques. For example, some color spaces like normalized RGB, CIE, YUV and XYZ detect clothe as a skin pixel because the skin color and the clothe color are the same. To overcome this problem, a new skin detection technique is proposed, namely, FDMP: Skin-Color Based Human Face Detection using Mixed Piece-wise Linear Decision Boundary and Template Matching Classifier, which combined the advantages in each color. The outputs obtained using single color produce better results. However, it is found that the outputs obtained from different color spaces when combined pixel-wisely, produce better results.

b) Parametric (Gaussian models) Techniques

The linear decision boundary classifiers use the fixed threshold values to segment the skin regions in color images. This resulted in several false positives for cases where the skin color and skin color are the same; misdetection by the algorithm happens in such cases marking the clothe as skin or vice-versa; this also happens for cases when the skin color and the background color are the same, classifying the background pixels as skin pixels. Hence, what is needed is a standard and better mathematical model to detect human skin in color images. A Gaussian model is used to efficiently detect human skin regions in color images. But the problem with the single Gaussian color model is that there is a probability for the occurrence of false detection. To overcome this problem, more than one Gaussian color model are used to detect human skin regions. Based on this premise, the
algorithm “FDMG - Human Face Detection in Color Images using Mixed Gaussian Color Models” is developed.

c) Non-parametric (Bayesian models) Approaches.

The linear decision boundary classifier and Gaussian models have their own shortcomings because the Gaussian model has certain problems as mentioned earlier and it does not produce better results using all commonly used color spaces. The results obtained depends on the selection of proper and appropriate color space and threshold values. The improper selection of color space and threshold values lead to false positives and true negatives. Hence, a statistical model like Bayesian model may be used to overcome these problems. Employing this idea, a new skin detection algorithm is proposed namely, FDSE: Human Face Detection using Statistical Models and Explicitly-defined Skin Region Classifiers using YCgCr model.

The family of Automatic Human Skin Detection techniques in color images applied to face detection resulted in this research work are given below:

[5] FDTM - Human Face Detection in Color Images using Skin Color and
5.1. Human Face Detection using Statistical Models and Explicitly-defined Skin Region Classifiers.

FDSE [84] is a new human skin detection technique using Bayesian, Gaussian and linear piecewise decision boundary classifiers in YCgCr color space. The new derived color space from YCbCr color performs well for skin detection techniques. The commonly used skin color classification methods are used. The results obtained using the three skin classification algorithms are compared. The Bayesian color model produces better results than Gaussian model. The skin detection method using linear decision boundary classifier in YCgCr color space produces better results than both Gaussian and Bayesian color models. Lip region detection is done to detect facial features using R/G and R/B color models.

Face detection is an attractive and important area in machine vision. It has a wide range of applications such as face recognition, video surveillance, face tracking and facial expression recognition [130]. Human faces have some unique features which distinguishes it from the background features in an image. Hence, skin-segmentation plays an important role in color based human-face segmentation. These segmented skin regions are further processed based on the facial features like mouth and eyes.

In FDSE, a new derived color space YCgCr is used to detect human skin regions [40, 41]. Any pixel is classified as a skin color if the chrominance components values are in the predefined range.

The first step in the face detection algorithm is human skin segmentation that eliminates as many non-skin pixels as possible so that the second stage of human
face detection is done with ease using facial features. The human skin is detected with the help of three skin classification algorithms namely Gaussian, Bayesian and explicitly defined skin cluster models [96]. The new derived color space YCgCr is effectively used to segment human skin regions in color images.

YCgCr is based on the application of colorimetric to television systems. The color conversion formulas for converting from RGB color space to YCgCr color spaces were given as follows:

\[
\begin{align*}
Y &= 0.256 \cdot R + 0.502 \cdot R + 0.096 \cdot B + 16 \\
C_g &= -0.317 \cdot R + 438 \cdot G - 0.121 \cdot B + 128 \\
C_r &= 0.438 \cdot R - 0.366 \cdot G - 0.071 \cdot B + 128
\end{align*}
\] (5-1)

FDSE proposes a new human skin detection algorithm with skin color-based pixel classification techniques namely Gaussian, Bayesian and linear decision boundary skin classifier using YCgCr color space. The method consists of two image processing steps. First, skin regions are separated from non-skin regions with the help of a new color space YCgCr color spaces. After that, the human face region within the skin regions is located using the technique used by Lewis [126]. The XM2VTS face database containing more than 100 color images together with manually prepared ground-truth are used for skin segmentation and face detection.

5.1.1 Architecture of FDSE System

The main advantage of converting the image to the YCgCr domain is that the influence of luminosity is removed. In the RGB domain, each component of the picture (red, green and blue) has a different brightness. However, in the YCgCr domain, all information about the brightness is given by the Y component, since the \( C_g \) (green) and \( C_r \) (red) components are independent from the luminosity. Therefore, the luminance information is easily de-embedded. The architecture of FDSE is
shown in figure 5.1. The color conversion formula is shown in equation (5-1).

5.1.2. Bayesian Classifier

The Bayesian decision rule for minimum cost is a well-established technique in statistical pattern classification [96], [111]. The class-conditional probability density function is estimated using histogram or parametric density estimation techniques.

The value of \( P_{\text{skin}}(c) \) computed in (5-2) is actually a conditional probability \( P(c|\text{skin}) \) - a probability of observing color \( c \), knowing that a skin pixel is seen:

\[
P_{\text{skin}}(c) = \frac{\text{skin}(c)}{\text{Norm}} \tag{5-2}
\]

where \( \text{skin}(c) \) give the value of the histogram bin, corresponding to the color vector \( c \) and Norm is the normalization coefficient (sum of all histogram values, or maximum bin value present). The normalization value of the lookup table bins constitutes the likelihood that the corresponding color corresponded to skin.

A more appropriate measure for skin detection is \( p(\text{skin}|c) \) - a probability of observing skin, given a concrete \( c \) color value. To compute this probability, the Bayes rule is used:

\[
p(c/\text{skin}) = (2\pi)^{-d/2}|C_s|^{-1/2}\exp\left[-1/2(c - m_s)^T C_s^{-1}(c - m_s)\right] \tag{5-3}
\]

\( p(c|\text{skin}) \) and \( P(c|\text{non-skin}) \) are directly computed from skin and non-skin color histograms. The prior probabilities \( p(\text{skin}) \) and \( p(\neg\text{skin}) \) are estimated from the overall number of skin and non-skin samples in the training set. An inequality \( p(\text{skin}|c) \geq \tau \), where \( \tau \) is a threshold value, is used as a skin detection rule. This means that \( p(\text{skin}) \) value affects only the choice of the threshold \( \tau \).

One could avoid computing (5-3) explicitly, if what is really needed is the comparison of \( p(\text{skin}|c) \) to \( p(\text{non-skin}|c) \), not their exact values.
Using (5-3) the ratio of $p(\text{skin} | c)$ to $p(\text{nonskin} | c)$ is written as:

$$
\frac{p(\text{skin} | c)}{p(\text{nonskin} | c)} = \frac{p(c | \text{skin})p(\text{skin})}{p(c | \text{nonskin})p(\text{nonskin})}
$$

(5-4)

Comparing (5-4) to a threshold produces the skin/non-skin decision rule.

After some manipulations equation (5-4) is rewritten as given in the next page:

$$
\frac{p(c / \text{skin})}{p(c / \text{nonskin})} \geq \tau
$$

(5-5)

The output image obtained using the Bayesian color model in YCgCr is...
shown in the figure 5.2.

5.1.3. Gaussian Classifiers

Terrillon et al. [109] compared Gaussian and Gaussian mixture models across nine chrominance spaces. Phung et al. [96] used eight color spaces to segment skin regions in the facial image in addition to Bayesian based and Gaussian based methods. The Bayesian classifier with the histogram technique has been used for skin detection by Jones and Rehg [37]. The class-conditional probability density function of skin colors is approximated by a parametric functional form, which is usually chosen to be a unimodal Gaussian, or a mixture of Gaussians [96]. In the case of the unimodal Gaussian model, the skin class conditional probability density function has the form:

\[
p(c/skin) = (2\pi)^{-d/2} |C_s|^{-1/2} \exp \left[ -1/2 (c - m_s)^T C_s^{-1} (c - m_s) \right]
\]

(5-6)

where \(d\) is the dimension of the feature vector, \(m_s\) is the mean vector and \(C_s\) is the covariance matrix of the skin class. If it is assumed that the non-skin class is uniformly distributed, the Bayesian rule in (5-6) is reduced to the following:

A color pixel \(c\) is considered as a skin pixel if

\[
(x - m_s)^T C_s^{-1} (x - m_s) \leq \tau
\]

(5-7)

where \(\tau\) is a threshold and the left hand side is the squared Mahalanobis distance. The resulting decision boundary is an ellipse in 2D space and an ellipsoid in 3D space. In FDSE, the approach of modeling both skin and non-skin distributions as unimodal Gaussians is investigated. In this case, it is easily shown that \(c\) is a skin
\[(c - m_s)^T C_s^{-1} (c - m_s) - (c - m_{ns})^T C_{ns}^{-1} (c - m_{ns}) \leq \tau \] (5-8)

where \(\tau\) is a threshold and \(m_{ns}\) and \(C_{ns}\) are the mean and the covariance of the non-skin class, respectively. The figure 5.2 shows the output results obtained using the Gaussian color model in YCgCr.

Figure 5.2 (a) Input Image (b) and (c) Skin Detection using Bayesian Model.
5.1.4. Explicitly-defined Skin Cluster Method

The pixel is classified as a skin pixel by applying a threshold operation to the given color image. The classification operation evaluates whether a pixel belongs to a class or not. The threshold values have a large influence on the segmentation results. A small threshold value will lead to a large number of small regions while with a large threshold value few large regions are calculated. The threshold values used in YCgCr color space is Cg [72,135] and Cr [130,212]. The output image obtained using the explicitly-defined skin color model in YCgCr is shown in the figure 5.4.

Figure 5.4 Skin Detection results using YCgCr Color Space based on Explicitly-defined Skin Regions.
5.1.5. Face Detection Algorithm using Lip Segmentation

A method used to identify lip is mentioned in [126], it is based on the lip’s red color spectrum. The pixel is classified as a lip pixel if the pixel value satisfies the following conditions:

\[
\begin{align*}
1.5 & \leq \frac{R}{G} \leq 2.5 \\
1.6 & \leq \frac{R}{B} < 2.7
\end{align*}
\]  

where R, G and B are the red, green and Blue color components, respectively that defines which values of R/G and R/B were considered as lip pixels.

After being processed with median filter, gray-level histogram equalization, figure 5.5 is the final binary image which shows ideal performance of equation (5-9) in detecting lip area. The figure 5.5 shows the lip detection results in R/G and R/B color spaces.

![Figure 5.5 Lip Detection Results using R/G and R/B Color Spaces based on Explicitly-defined Skin Cluster Method.](image)

It is suggested that equation (5-9) is a kind of filter with parameters (1.5, 2.5) in identifying lip area. Its rationale is interpreted as eliminating skin area based on the proportion of red color spectrum components. Experiments in detecting lip with R/G and R/B filters show that R/G method can achieve 96% accuracy (true positive) under simple background. But it fail in complex environment, for example, it is easily influenced by some red objects. The face detection results are shown in Figure 5.6.
5.1.6 Algorithm of FDSE

Step 1: The input color image is converted into a skin-likelihood image by applying Gaussian model. The skin-likelihood image represents the probability of the pixel being a skin pixel.

Step 2: The skin likelihood image is converted into a binary image using an adaptive threshold.

Step 3: The input image is converted into a skin segmented binary image using Bayesian color model.

Step 4: The explicitly-defined skin cluster method is used to segment human skin regions in color images.

Step 5: The best output image is selected from the images obtained from the skin detected binary images obtained using Gaussian, Bayesian and explicitly-defined skin cluster models.

Step 6: The presence of a facial image is verified by checking whether the given color image has a lip region or not. If so, the boundaries of a face image are determined. The face image is marked with a rectangle.
5.2 Human Face Detection in Color Images using Pixel Based Skin Color Detection Techniques

FDPS [83] is human skin detection technique using the Bayesian color model. The performance of the Bayesian color model is compared using RGB, YCbCr, YUV, YIQ, YES, YESRBYB, YESRGB, XYZ, HSV, HSI, HLS, HCl, Normalized RGB, CIE-Lab, CIE-Luv, UCS and KL transform. This technique is the best in detecting human skin regions in color images.

5.2.1 The Architecture of FDPS System

FDPS gives a comparative study on the human skin detection algorithm using RGB, YCbCr, YUV, YIQ, YES, YESRBYB, YESRGB, XYZ, HSV, HSI, HLS, HCl, Normalized RGB, CIE-Lab, CIE-Luv, UCS and KL transform based on Bayesian color model. The architecture of FDFP system is shown in figure 5.7.

![Figure 5.7 FDPS Face Detection System](image)

5.2.2 Human Skin Detection using Pixel-wise Fusion of Color Spaces

In the past, different color spaces had been used in detecting human skin regions in color images. FDPS investigates how the choice of the color space and the use of chrominance channels affect skin segmentation. Several color spaces are used in digital image processing. The color spaces used are RGB, YCbCr, YUV, YIQ,
YES, YESRBYB, YESRGB, XYZ, HSV, HSI, HLS, HCl, Normalized RGB, CIE-Lab, CIE-Luv, UCS, and KL transform. The description about the different color spaces is discussed in addition to the color conversion techniques.

RGB (Red Green Blue) color space is an additive, device dependent color system based on tri-chromatic theory. Often found in systems that use a CRT to display images. It is easy to implement but non-linear with visual perception.

YCbCr is an encoded nonlinear RGB signal, commonly used by European television studios and for image compression work. Color is represented by luminance, constructed as a weighted sum of the RGB values, and two color difference values Cr and Cb that are formed by subtracting luminance from red and blue components. Y is the luminance information. The color conversion formula used to convert from RGB to YCbCr is given in the equation (5-10).

\[
Y = 0.299 R + 0.587 G + 0.114 B \\
Cr = R - Y \\
Cb = B - Y
\]  

(5-10)

The YUV model defines a color space in terms of one luminance and two chrominance components. The YUV color model is used in the PAL, NTSC, and SECAM composite color video standards. YUV models human perception of color more closely than the standard RGB model used in computer graphics hardware. Y stands for the luma component (the brightness) and U and V are the chrominance (color) components [105].

\[
\begin{align*}
Y &= 0.299 R + 0.587 G + 0.114 B \\
U &= -0.147 R - 0.289 G + 0.437 B \\
V &= 0.615 R - 0.515 G - 0.100 B
\end{align*}
\]  

(5-11)

YIQ color model is designed to separate chrominance from luminance. The Y-channel contains luminance information which is sufficient for black-and-white
television sets while I and Q channels (in-phase and in-quadrature) carried the color information [33]. The color conversion formula used convert from RGB to YIQ is given in the equation (5-12).

\[

text{Y} = 0.299 \ast R + 0.587 \ast G + 0.114 \ast B \\
I = 0.596 \ast R - 0.274 \ast G - 0.322 \ast B \\
Q = 0.212 \ast R - 0.523 \ast G + 0.322 \ast B
\]

(5-12)

In the YES color space, the luminance component (Y) is a weighted sum of the RGB values, while the chrominance factors are spectral differences: The signal in the E factor is proportional to the difference of the red and green color channels, while the S color factor is proportional to yellow minus blue. Y represents the luminance component and E and S denote the chrominance factors. The YES color space can be transformed from RGB coordinates. The corresponding transformation from RGB color model to YES color model is given below [33]:

\[

text{Y} = 0.253 \ast R + 0.684 \ast G + 0.063 \ast B \\
E = 0.500 \ast R - 0.500 \ast B + 0.000 \ast B \\
S = 0.250 \ast R + 0.250 \ast G - 0.500 \ast B
\]

(5-13)

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

Normalized RGB is a representation that is easily obtained from the RGB values by a simple normalization procedure [51]:

\[

text{r} = \frac{R}{(R + G + B)} \\
\text{g} = \frac{G}{(R + G + B)} \\
\text{b} = \frac{B}{(R + G + B)}
\]

(5-14)

As the sum of the three normalized components is known (r + g + b = 1), the third component does not hold any significant information and can be omitted, reducing the space dimensionality. The remaining components are often called "pure
colors”, for the dependence of r and g on the brightness of the source RGB color is diminished by the normalization.

The intuitiveness of the Hue-saturation based color space components and explicit discrimination between luminance and chrominance properties made these color spaces popular in the works on skin color segmentation. Hue defines the dominant color (such as red, green, purple and yellow) of an area; saturation measures the colorfulness of an area in proportion to its brightness. The “intensity”, “lightness” or “value” is related to the color luminance.

Thus by means of the equations given in (5-15) one can be able to detect the skin regions from HSV images [49].

\[
H = \arccos \frac{1}{2} \left( \frac{(R - G) + (R - B)}{\sqrt{((R - G)^2 + (R - B)(G - B))}} \right)
\]

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

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

(5-15)

The KL transform is very useful to shift and rotate data set in coordinate space. It not only turns three linear interrelated components into linear non-interrelated ones, but also makes their variances the least. But skin information is stored inside of the three components, which results in difficulties to face detection [129].

\[
K_1 = 0.666^*R + 0.547^*G + 0.507^*B
\]

\[
K_2 = -0.709^*R + 0.255^*G + 0.657^*B
\]

\[
K_3 = 0.230^*R - 0.797^*G + 0.558^*B
\]

(5-16)

XYZ color space is another color space used in skin detection. The formula used to convert from RGB to XYZ color space is given as follows [133]:

132
A color can be described as a mixture of three other colors or "Tristimuli". Typically RGB for CRT based systems (TV, computer) or XYZ (fundamental measurements). The amounts of each stimulus define the color. However, it is frequently useful to separate the color definition into "luminance" and "chromaticity". Lower case is always used to signify chromaticity co-ordinates; upper case always signifies tristimulus values (or amounts of the primaries).

The CIE XYZ (1931) system is at the root of all colorimetry. It is defined such that all visible colors can be defined using only positive values, and, the Y value is luminance. Consequently, the colors of the XYZ primaries themselves are not visible. A color defined in this system is referred to as Yxy. A third co-ordinate, z, can also be defined but is redundant since \( x + y + z = 1 \) for all colors.

\[
x = \frac{X}{X + Y + Z} \\
y = \frac{X}{X + Y + Z}
\]

CIE-YUV (1960) is a linear transformation of Yxy, in an attempt to produce a chromaticity diagrams in which a vector of unit magnitude (difference between two points representing two colors) is equally visible at all colors. Y is unchanged from XYZ or Yxy. Difference non-uniformity is reduced considerably, but not enough. A third co-ordinate, w, can also be defined but is redundant.

\[
u = \frac{2x}{6y - x + 1.5} \\
v = \frac{3y}{6y - x + 1.5}
\]

CIE L*a*b* is based directly on CIE XYZ (1931) and is another attempt to linearise the perceptibility of unit vector color differences. Again, it is non-linear, and the conversions are still reversible. Coloring information is referred to the color
of the white point of the system, subscript n. The non-linear relationships for $L^* a^*$ and $b^*$ are the same as for CIE LUV and are intended to mimic the logarithmic response of the eye [3].

\[
L' = \begin{cases} 
116(Y/Y_n)^{1/3} - 16, & \text{if } (Y/Y_n) > 0.008856 \\
903.3(Y/Y_n), & \text{if } (Y/Y_n) \leq 0.008856 
\end{cases}
\]

(5-20)

\[
a^* = 500(f(X/X_n) - f(Y/Y_n)) \\
b^* = 200(f(Y/Y_n) - f(Z/Z_n))
\]

(5-21)

where \( f(t) = \begin{cases} 
t^{1/3}, & \text{if } t > 0.008856 \\
7.787 \times 16 + 116, & \text{if } t \leq 0.008856 
\end{cases}\)

and

\[
\begin{align*}
X_n &= 95.05 \\
Y_n &= 100 \\
Z_n &= 108.88
\end{align*}
\]

(5-22)

5.2.3. Bayesian Classifier

The Bayesian decision rule for minimum cost was a well-established technique in statistical pattern classification [96], [111]. The class-conditional probability density function is estimated using histogram or parametric density estimation techniques.

The value of $p_{\text{skin}}(c)$ computed in (5-23) is actually a conditional probability $p(c|\text{skin})$ - a probability of observing color $c$, knowing that a skin pixel is seen:

\[
p_{\text{skin}}(c) = \frac{\text{skin}(c)}{\text{Norm}}
\]

(5-23)

where $\text{skin}(c)$ gives the value of the histogram bin, corresponding to the color vector $c$ and Norm is the normalization coefficient (sum of all histogram values, or maximum bin value present. The normalization value of the lookup table bins constituted the likelihood that the corresponding color corresponded to skin.
A more appropriate measure for skin detection is \( p(\text{skin}|c) \) - a probability of observing skin, given a concrete \( c \) color value. To compute this probability, the Bayes rule is used:

\[
p(\text{skin} | c) = \frac{p(c | \text{skin})p(\text{skin})}{p(c | \text{skin})p(\text{skin}) + p(c | \text{nonskin})p(\text{nonskin})}
\]  

(5-24)

\( P(c|\text{skin}) \) and \( P(c|\text{nonskin}) \) are directly computed from skin and non-skin color histograms. The prior probabilities \( p(\text{skin}) \) and \( p(\neg \text{skin}) \) are estimated from the overall number of skin and non-skin samples in the training set. An inequality \( p(\text{skin}|c) \geq \tau \), where \( \tau \) is a threshold value, is used as a skin detection rule. This means that \( p(\text{skin}) \) value affects only the choice of the threshold \( \tau \).

One can avoid computing (5-24) explicitly, if what is really needed is the comparison of \( P(\text{skin}|c) \) to \( P(\text{nonskin}|c) \), not their exact values.

Using (5-24) the ratio of \( P(\text{skin}|c) \) to \( P(\text{nonskin}|c) \) is written as:

\[
\frac{p(\text{skin} | c)}{p(\text{nonskin} | c)} = \frac{p(c | \text{skin})p(\text{skin})}{p(c | \text{nonskin})p(\text{nonskin})}
\]  

(5-25)

Comparing (5-25) to a threshold produced the skin/non-skin decision rule. After some manipulations is rewritten as:

\[
\frac{p(c / \text{skin})}{p(c / \text{nonskin})} \geq \tau
\]  

(5-26)

5.2.4. Gaussian Classifiers

Terrillon et al. [109] compared Gaussian and Gaussian mixture models across nine chrominance spaces. Phung et al. [96] used eight color spaces to segment skin regions in the facial image in addition to Bayesian based and Gaussian based methods. The Bayesian classifier with the histogram technique had been used for skin detection by Jones and Rehg [37]. The class-conditional probability density
function of skin colors was approximated by a parametric functional form, which was usually chosen to be a unimodal Gaussian, or a mixture of Gaussians [96]. In the case of the unimodal Gaussian model, the skin class conditional probability density function has the form:

\[
p(c \mid \text{skin}) = (2\pi)^{-d/2} |C_s|^{-1/2} \exp\left[ -1/2 (c - m_s)^T C_s^{-1} (c - m_s) \right]
\]  

(5-27)

where \( d \) was the dimension of the feature vector, \( m_s \) is the mean vector and \( C_s \) is the covariance matrix of the skin class. If it is assumed that the non-skin class is uniformly distributed, the Bayesian rule in (5-27) reduced to the following:

A color pixel \( c \) is considered as a skin pixel if

\[
(x - m_s)^T C_s^{-1} (x - m_s) \leq r
\]

(5-28)

where \( r \) is a threshold and the left hand side is the squared Mahalanobis distance. The resulting decision boundary is an ellipse in 2D space and an ellipsoid in 3D space. In FDSE, the approach of modeling both skin and non-skin distributions as unimodal Gaussians is investigated. In this case, it is easily shown that \( c \) is a skin pixel if

\[
(c - m_s)^T C_s^{-1} (c - m_s) - (c - m_{ns})^T C_{ns}^{-1} (c - m_{ns}) \leq r
\]

(5-29)

where \( r \) is a threshold and \( m_{ns} \) and \( C_{ns} \) are the mean and the covariance of the non-skin class, respectively.

5.2.5. Algorithm of FDPS

Step 1: The given input image is converted from RGB to RGB, YCbCr, YUV, YIQ, YES, YESRBYB, YESRGB, XYZ, HSV, HSI, HLS, HCI, Normalized RGB, CIE-Lab, CIE-Luv, UCS, and KL transform color spaces used.
Step 2: The input image is converted into a skin segmented binary image showing skin and non-skin regions by using the above mentioned color spaces based on the Bayesian, Gaussian and explicitly-defined skin cluster color model.

Step 3: The facial region boundaries are determined and marked.

5.3. Skin Color-Based Human Face Detection using Mixed Piece-wise Linear Decision Boundary and Template Matching Classifiers.

FDMP [127] is a novel human skin detection technique in color images using mixed piece-wise linear decision boundary classifier using eighteen chrominance spaces. The aim of this algorithm is to detect human skin regions efficiently by combining the positive aspects of each color space and each color space component. The color spaces like HSV, YCbCr, CIE used with piece-wise linear decision boundary classifier produce better results when they are separately used. But when these color spaces are combined to segment human skin regions produce best results. The output results contains all the facial features in the face regions. The segmented binary image is further used to efficiently detect facial features to detect human face regions in the images given. In order to verify whether the skin regions contain any facial regions, the golden ratio is used. The golden ratio is the ratio of the height of the skin region to width of the skin region. FDMP examines and combines eighteen color spaces to segment human skin in color images. To support this study, XM2VTS face database containing more than 50 color images are used. In addition Caltech face database, Indian Face Database and Asian Face database are used for skin segmentation and face detection.

A number of research papers using skin color pixel classification approaches had been reported. Vezhnevets et al. [111] gave a comprehensive comparative analysis of pixel-based human skin detection methods. The skin detection techniques
classified each image pixel into skin and non-skin categories based on the pixel color [96], [11], [48]. The reason for using pixel color as a feature to detect human skin regions was that the human skin color has very consistent colors which are distinct from the colors of other objects. Brand et al [7] used three approaches to segment human skin using pixel-wise skin classification. Chai et al. used skin color map in videophone to segment face regions using RGB, YCbCr and HSV color spaces [11]. Zarit et al. compared five color models to classify human skin color [122, 123]. Garcia et al. used HSV and YCbCr color space to detect human face using quantized skin color regions merging and wavelet packet analysis [8, 9]. Phung et al. [96] used eight color spaces to segment human skin regions in the facial image in addition to Bayesian, Gaussian skin classification algorithms based on the skin pixel color information. The method of segmenting skin and face regions in the color image using template matching technique was suggested in [54], [115].

5.3.1. Architecture of FDMP System

FDMP combines the positive aspects of eighteen color spaces to segment human skin regions. The input image is converted into all the other eighteen other color spaces. The human skin regions are segmented using the explicit skin cluster classifier resulting in binary images. Eighteen output results obtained using eighteen color spaces are combined pixel-wise to produce a single final skin segmented binary image containing all the facial features that can be used for the next post processing step of face detection stage. The co-ordinates of the facial regions in the given image are determined using the boundaries and rectangle is drawn in the original color image.
5.3.2. Color Space Conversions

In the past, different color spaces had been used in detecting human skin regions in color images. FDMP investigates how the choice of the color space and the use of chrominance channels affect skin segmentation. Several color spaces were used in digital image processing. But many of them share similar characteristics. Hence, in this study, eighteen representative color spaces which are commonly used in the image processing field are focused. The color spaces used were RGB, YCbCr, YUV, YIQ, YES, YESRB, YESRGB, XYZ, HSV, HSI, HLS, HCI, Normalized RGB, CIE-Lab, CIE-Luv, UCS, KL, and YCgCr. The description about the different color spaces is discussed in addition to the color conversion techniques in section 5.2.2.

5.3.3. Explicitly-defined Skin Cluster Techniques

In this category of classifiers, skin and non-skin colors are separated using a piecewise linear decision boundary. Mei-Juan Chen[65] used YCbCr color space to detect skin color. Sobottka and Pitas [46] proposed a set of fixed skin thresholds in the HS plane. Jure Kovac [44] used RGB color space to detect face region in 2D and 3D color spaces. Lamiaa Mostafa, [51] used normalized RGB color space to segment face region in color images. Chai and Ngan [11] proposed a face segmentation algorithm for a videophone application in which a fixed-range skin color map in the CbCr plane was used. Juan Jose’ De Dios et al. proposed a new color space to segment face image in color images [40]. Stephen Karungaru, Minoru Fukumi and Norio Akamatsu used YUV color space to segment human skin [105]. Xin He, Zhi-Ming Liu, Ji-Liu Zhou used YIQ color space to detect human face in color images [128]. Hsin-Chia Fut P.S. Lai, R.S. Lou, H.-T. Paot used YES color space to detect face and eyes [33].
Fusion of outputs obtained using eighteen color spaces

Figure 5.8. FDMP Face Detection Algorithm

These approaches are based on the observation that skin chrominance, even across different skin types, have a small range, whereas skin luminance varied widely. The color spaces used are RGB, YCbCr, YUV, YIQ, YES, YESRBYB, YESRGB, XYZ, HSV, HSI, HLS, HCI, Normalized RGB, CIE-Lab, CIE-Luv, UCS, KL, and YCgCr. But the previous finding by Min C. Shin et. al. was that no color space was considered as universal because color could be interpreted and modeled in different ways [131].
In the past, different color spaces had been used for skin segmentation. In some cases, color classification was done using only pixel chrominance because it was expected that skin segmentation might become more robust to lighting variations if pixel luminance was discarded. The choice of the color space is important for many computer vision algorithms.

5.3.4. Mixed Explicitly-defined Skin Cluster Techniques

The method proposed uses eighteen chrominance spaces to detect human skin regions in color images and the performance of different color spaces with application to skin detection are compared. Even though the chrominance spaces like HSV, YCbCr, and CIE are used with piece-wise linear decision boundary classifier produces good results when they are separately used. But when these color spaces are combined to segment human skin produce better results.

5.3.5 Algorithm of FDMP

Step 1: The input image is converted into all the other eighteen other color spaces.

Step 2: The human skin is segmented using the explicit skin cluster classifier resulting in binary images.

Step 3: Eighteen output results obtained using eighteen color spaces are combined pixel-wise to produce a single final skin segmented binary image containing all the facial features that can be used for the next post processing step of face detection stage.

Step 4: The co-ordinates of the facial regions in the given image are determined using the boundaries and rectangle is drawn in the original color image.
5.4 Human Face Detection in Color Images using Mixed Gaussian Color Models

FDMG [86] is a human skin segmentation technique using mixed Gaussian models and gives a comparative analysis of few mixed Gaussian color models using four color spaces. Five combinations of two color space are used in Gaussian model. This new human face detection algorithm involves two stages: applying mixed Gaussian skin color model to segment human skin regions and using facial feature detection technique to detect human face regions in color images. RGB color space do not differentiate the human skin color and the clothes when skin color and clothe color are the same. YIQ color space produces better results than RGB. YCbCr color space produces better results than RGB, YIQ. But YUV color space produces the better results when used to segment skin regions in color images using mixed Gaussian color models. These inferences are derived from the visual effects. This algorithm is quite practical and faster in comparison to other techniques such as neural networks.

5.4.1 The Architecture of FDMG System

Input image is converted from RGB to YCbCr, YIQ, YUV color spaces. Gaussian color model is used to find the skin-likelihood image. The skin segmented binary image is obtained using the adaptive threshold. The skin detected images are obtained using RGB, YCbCr, YIQ, YUV color spaces. The output images and its correct detection rates are compared. The output images are obtained using a combination of two color spaces. That is, the output image is obtained by fusing the two output images pixel-wise for the color space combinations, RGB-YUV, RGB-YCbCr, RGB-YIQ, YCbCr-YUV and YCbCr-YIQ. In order to detect facial features like eyes and lips, two separate eyes maps are built. First, eye map is built using
chrominance components. Second, eye map is built using luminance component. These two eye maps are then merged into a single eyes map. The color of the mouth region contains stronger red component and weaker blue component than other facial regions. Hence, the chrominance component $C_r$ is greater than $C_b$ in the mouth region. The mouth has a relatively low response in the feature, but it has a high response in. Then the mouth map is constructed. The Architecture of FDMG system is shown in figure 5.9.

![Figure 5.9](image)

**Figure 5.9. The Architecture of FDMG System**

### 5.4.2. Human Skin Detection using Mixed Gaussian Color Models

The color information is used to segment face regions in color images for the past twenty years. Most publications have shown that color is a powerful descriptor that had practical use in the extraction of the face detection.

The class-conditional probability density function of skin colors is approximated by a parametric functional form, which is usually chosen to be a unimodal Gaussian, or a mixture of Gaussians [26]. In the case of the unimodal Gaussian model, the skin class conditional probability density function have the form:
p(c / skin) = (2π)^{-d/2} |C_s|^{-1/2} \exp\left[-1/2 (c - m_s)^T C_s^{-1} (c - m_s)\right] \quad (5-30)

where d is the dimension of the feature vector, \( m_s \) is the mean vector and \( C_s \) is the covariance matrix of the skin class. If it is assumed that the non-skin class is uniformly distributed, the Bayesian rule in (5-30) reduced to the following: a color pixel \( c \) is considered as a skin pixel if

\[ (c - m_s)^T C_s^{-1} (c - m_s) \leq \tau \quad (5-31) \]

where \( \tau \) is a threshold and the left hand side is the squared Mahalanobis distance. The resulting decision boundary is an ellipse in 2D space and an ellipsoid in 3D space. In this study, the approach of modeling both skin and non-skin distributions are investigated as unimodal Gaussians. In this case, it is shown that \( c \) is a skin pixel if

\[ (c - m_s)^T C_s^{-1} (c - m_s) - (c - m_{ns})^T C_{ns}^{-1} (c - m_{ns}) \leq \tau \quad (5-32) \]

where \( \tau \) is a threshold and \( m_{ns} \) and \( C_{ns} \) are the mean and the covariance of the non-skin class, respectively. Another approach is to model both skin and non-skin distributions as Gaussian mixtures [26, 111]:

\[
\begin{align*}
p(c / skin) &= \sum_{i=1}^{N_s} \omega_{si} g\left(c; m_{si}, C_{si}\right) \\
p(c / nonskin) &= \sum_{i=1}^{N_{ns}} \omega_{nsi} g\left(c; m_{nsi}, C_{nsi}\right)
\end{align*}
\]

(5-33) (5-34)

The parameters of a Gaussian mixture (i.e., weights \( \omega \), means \( m \), covariance \( C \)) were typically found using the Expectation/Maximization algorithm.

Based on the skin color areas in the RGB, YUV, YCbCr color space and YIQ color space, two Gaussian models are utilized for representing the skin color model with mean and covariance.
Let \( \{\mu, \sigma\} \) be as the mean and variance of color Gaussian model based on the given color space. Based on the mixture model, the likelihood ratio of skin color areas is calculated. Let \( p(x, y) \) be the pixel value in the image, then the proposed skin color detection technique is written as formula (5-35):

\[
p(x, y) = \begin{cases} 
\frac{1}{\sqrt{2\pi\sigma_{\text{colorspace}}}} e^{-\frac{(p(x, y) - \mu_{\text{colorspace}})^2}{2\sigma_{\text{colorspace}}^2}} & \text{if} p(x, y) \in \text{skin} \\
0 & \text{if} p(x, y) \notin \text{skin} 
\end{cases}
\]  

(5-35)

Among all the stages, this first stage is the most important stage based on the proposed model of skin color. The color segmentation has to remove as many pixels as possible that are unlikely to belong to the skin region. However, the result of color segmentation is the detection of pixels in a skin area and may also include other areas where the distribution of pixels coincide with the proposed model of skin color areas.

5.4.3. Eyes Map

In order to detect facial features like eyes and lips, two separate eyes maps are built [128]. First, eye map is built using chrominance components. Second, eye map is built using luminance component. These two eye maps are then merged into a single eyes map. The eye maps are built using the observation that high \( C_b \) and low \( Cr \) values are found around the eyes. It is constructed by

\[
FF_{EM} = \frac{1}{3}(C_b^2 + \tilde{Cr}^2 + C_b / C_r)
\]

(5-36)

where \( C_b \), \( \tilde{Cr} \) and \( C_b / C_r \) are normalized to the range \([0, 255]\) and is the negative of \( Cr \) (i.e., \( 255 - Cr \)). Figure 5.10 shows the result of eyes map from the chrominance component. Since the eyes usually contain both dark and bright pixels in the luminance component, grayscale morphological operators (e.g., dilation and erosion)
are designed to emphasize brighter and darker pixels in the luminance component around eyes regions.

Figure 5.10. (a) Input Image (b) Chrominance Eye Map

FDMG uses grayscale dilation and erosion with a hemispheric structuring element to construct the eyes map from the luminance as follows:

$$L_{MEM} = \frac{I(x,y) \oplus g(x,y)}{I(x,y) \ominus g(x,y) + 1}$$ (5-37)

where the grayscale dilation $I(x,y) \oplus g(x,y) = \{[g(x,y)]_z \cap I(x,y) \neq \emptyset \}$ is based on obtaining the reflection of $g(x,y)$ about its origin and shifting this reflection by $z$. The dilation of $I(x,y)$ by $g(x,y)$ then is the set of all displacements, $z$, which requires that $g'(x,y)$ and $I(x,y)$ is overlapped by at least one element. One of applications of dilation is for bridging gaps. The grayscale erosion $I(x,y) \ominus g(x,y) = \{[g(x,y)]_z \cap I(x,y) \neq \emptyset \}$ is the set of all points $z$ such that $g(x,y)$, translated by $z$, is contained in $I(x,y)$. One of the uses of erosion is for eliminating irrelevant detail in terms of size from a binary image. In the expressions (5-37), denominator added one is to turn away dividing by zero. The eyes map from the chroma is enhanced by histogram equalization, which involves transforming the intensity values so that the histogram of the output image is
approximately matched a specified histogram, and then combined with the eye map from the luminance by an AND operation, i.e., $FF_{EM} = (FF_{EM}) \text{ AND } (LM_{EM})$. The result of eyes map is then dilated, masked, and normalized to brighten both the eyes and suppressed other facial areas, as that shown in Figure 5.11. The locations of the eyes candidates are initially estimated from the pyramid decomposition of the eyes map, and then refined using iterative thresholding and binary morphological closing on this eyes map.

5.4.4. Mouth map

The color of mouth region contains stronger red component and weaker blue component than other facial regions [128]. Hence, the chrominance component $C_r$ is greater than $C_b$ in the mouth region. The mouth has a relatively low response in the feature, but it has a high response in. Then the mouth map is constructed as follows:

$$MouthMap = C_r^2 \times (C_r^2 - \eta \times C_r / C_b)$$  \hspace{1cm} (5-38)$$

$$\eta = 0.95 \times \frac{1}{n} \sum_{(x,y) \in FG} C_r(x,y)^2$$  \hspace{1cm} (5-39)$$
where both and are normalized to the range \([0, 255]\), and \(n\) is the number of pixels within the face mask, \(FG\). The parameter \(\eta\) is estimated as a ratio of the average \(C_r^2\) to the average \(C_h/C_r\). Figure 5.12 shows the result of mouth map and the eye and mouth map.

![Mouth Map and Eye-Mouth Map](image)

Figure 5.12 (a) The Mouth Map (b) The Eye and Mouth Map.

The coordinates of the skin region are determined and the facial region is marked with a rectangle as shown in figure 5.13.

![Face Detected Image](image)

Figure 5.13 Face Detected Image

5.4.5. Algorithm of FDMG System

Step 1: Input image is converted from RGB to YCbCr, YIQ, YUV color spaces.
Step 2: Gaussian color model is used to find the skin-likelihood image.

Step 3: The skin segmented image is obtained using the adaptive threshold.

Step 4: The skin detected images are obtained using RGB to YCbCr, YIQ, YUV color spaces. The output images and its correct detection rates are compared.

Step 5: The output images are obtained using a combination of two color spaces. That is, the output image is obtained by fusing the two output images pixel-wise for the color space combinations, RGB-YUV, RGB-YCbCr, RGB-YIQ, YCbCr-YUV and YCbCr-YIQ.

Step 6: In order to detect facial features like eyes and lips, two separate eyes maps are built. First, eye map is built using chrominance components. Second, eye map is built using luminance component. These two eye maps are then merged into a single eyes map.

Step 7: The color of mouth region contains stronger red component and weaker blue component than other facial regions. Hence, the chrominance component Cb is greater than Cb in the mouth region. The mouth has a relatively low response in the feature, but it has a high response in. Then the mouth map is constructed.

5.5. Human Face Detection in Color Images using Skin Color and Template Matching Models for Multimedia on the Web

FDTM [85] is a new skin detection technique using skin color-based pixel classification strategy namely explicit skin cluster classifier. The method consists of three image processing steps. First, YCbCr color space is used to segregate skin regions using a modified linear decision boundary skin classification algorithm. The second skin regions are segregated from non-skin regions with the help of YCbCr
and YIQ color spaces [65]. The third skin detection method uses YCbCr, YIQ and HSV color space. Finally, the commonly used color spaces like, YCbCr, HSV, RGB, normalized RGB and YIQ are combined to segment human skin regions in the color image. These three approaches have been compared with the help of the output images and the correct detection rates. The template matching technique is used to verify the presence of the facial regions in color images [54, 12]. The XM2VTS face database containing more than 50 color face images downloaded from internet are used in segmenting skin regions in color images. In addition, manually prepared ground-truth images are used for skin segmentation and face detection. The other color face databases used are Caltech Face Database, Postech Faces '01, and Indian Face Database.

5.5.1 Color Space Conversions

FDTM [85] investigates how the choice of the color space and the use of chrominance channels affect skin segmentation. Several color spaces are used in digital image processing. But many of them share similar characteristics. The description about the different color spaces is discussed in addition to the color conversion techniques.

The intuitiveness of the Hue-saturation based color space components and explicit discrimination between luminance and chrominance properties make these color spaces suitable for skin color segmentation. Hue defines the dominant color (such as red, green, purple and yellow) of an area; saturation measures the colorfulness of an area in proportion to its brightness. The "intensity", "lightness" or "value" is related to the color luminance.
The conversion formula for HSV color space from RGB is given below [5-40]:

\[
H = \arccos \left( \frac{1}{2} \left( \frac{(R-G) + (R-B)}{\sqrt{(R-G)^2 + (R-B)(G-B)}} \right) \right)
\]

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

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

(5-40)

YCbCr is an encoded nonlinear RGB signal, commonly used by European television studios and for image compression work. Color is represented by luminance, constructed as a weighted sum of the RGB values, and two color difference values Cr and Cb that are formed by subtracting luminance from RGB red and blue components. Y is the luminance information. Cb and Cr are the chrominance information.

The formula used to convert from RGB to YCbCr color format is given in equation (5-41):

\[
\begin{align*}
Y &= 0.257 \times R + 0.504 \times G + 0.098 \times B + 16 \\
Cb &= 0.439 \times R - 0.368 \times G - 0.071 \times B + 128 \\
Cr &= -0.148 \times R - 0.291 \times G + 0.439 \times B + 128
\end{align*}
\]

(5-41)

YIQ color model is designed to separate chrominance from luminance. The Y-channel contains luminance information which is sufficient for black-and-white television sets while I and Q channels (in-phase and in-quadrature) carried the color information [131].

\[
\begin{align*}
Y &= 0.30 \times R + 0.59 \times G + 0.11 \times B \\
I &= 0.60 \times R - 0.28 \times G + 0.31 \times B \\
Q &= 0.21 \times R - 0.51 \times G + 0.31 \times B
\end{align*}
\]

(5-42)
Normalized RGB is a representation that is easily obtained from the RGB values by a simple normalization procedure [51]:

\[ r = \frac{R}{R + G + B} \]
\[ g = \frac{G}{R + G + B} \]
\[ b = \frac{B}{R + G + B} \]  

(5-43)

5.5.2 Architecture of FDTM System

FDTM proposes three skin detection strategies using piecewise linear boundary skin classifier techniques. The first skin detection technique uses YCbCr color space and \( \alpha \) to define two threshold values to detect human skin regions in color images. The second skin detection strategy uses YCbCr and YIQ to segment skin regions in color images. Similarly, the third skin classification strategy uses the commonly used color spaces HSV, YCbCr and YIQ are used to segment human skin regions based on piecewise linear decision boundary classifier algorithm. The outputs from these three skin classification algorithms are compared. The experimental results have shown that the second method produces better results than the other two skin detection techniques.

5.5.3 Human Skin Detection Techniques

The skin detection is regarded as a standard two-class problem, taking a color image as input and producing a binary image as output. Pixel-based skin detector works by sequentially and independently analyzing each image pixel’s color and labeling the pixel as skin or non-skin. A good skin color pixel classification approach should provide coverage of all different human skin color types like whitish, blackish and brownish.
The fixed threshold values do not produce good results in skin detection. Therefore, the threshold values are determined using the mean and standard deviation of the image pixel values. The first skin detection techniques uses the mean and standard deviation of a pixel values. The pixel in any color face image is classified as a skin pixel if the value of Cb and Cr are in the range from minimum and maximum threshold values. The linear decision boundary classification technique used to segment human skin is given as shown in the next page:

\[
\begin{align*}
Cb &> \text{Min } Cb \text{ and } Cb < \text{Max } Cb \\
Cr &> \text{Min } Cr \text{ and } Cr < \text{Max } Cr
\end{align*}
\] (5-44)

where

\[
\begin{align*}
\text{Min } Cb &= \text{mean}(Cb) - \text{std}(Cb) * \alpha \\
\text{Min } Cr &= \text{mean}(Cr) - \text{std}(Cr) * \alpha
\end{align*}
\] (5-45)

\[
\begin{align*}
\text{Min } Cb &= \text{mean}(Cb) - \text{std}(Cb) * \alpha \\
\text{Min } Cr &= \text{mean}(Cr) - \text{std}(Cr) * \alpha
\end{align*}
\] (5-46)

With appropriate threshold values of Cb, Cr and \( \alpha \), the color face images can be transformed to a binary image showing skin regions and non-skin regions.

The second skin detection method uses two color spaces to segment a skin region in the color image given. YCbCr and YIQ are commonly used color spaces in televisions. According to this method, a pixel is classified as a skin pixel if the value of color components is in the range between minimum and maximum threshold values. The linear decision boundary classification technique used to segment human skin is given as:

\[
\begin{align*}
(Cb > 85) \text{ and } (Cb < 135), \\
(Cr > 135) \text{ and } (Cr < 180), \\
(I > 20) \text{ and } (I <= 90)
\end{align*}
\] (5-47)
Figure 5.14 Architecture of FDTM System

The third method uses the three color spaces to detect human skin regions in color images. The pixel is classified as a skin pixel if the value of color components is in the range between minimum and maximum threshold values. The linear decision boundary classification technique used to segment human skin is given as:
With appropriate threshold values of the different color components, the color images can be transformed to a binary image showing skin regions and non-skin regions.

The fourth skin detection method uses five color spaces to detect human skin regions in color images using normalized RGB, HSV, YCbCr, YIQ and RGB. The linear decision boundary skin classification conditions are shown in the equation (5-49).

\[
\begin{align*}
& (H[i, j] \geq 0) \text{ and } (H[i, j] \leq 50), \\
& (S[i, j] > 0.23) \text{ and } (S[i, j] < 0.68), (V[i, j] > 0.4000), \\
& (Cb > 85) \text{ and } (Cb < 135), (Cr > 135) \text{ and } (Cr < 180), \\
& (I > 170) \text{ and } (I < 170), (Q > 75) \text{ and } (Q < 200)
\end{align*}
\]

5.5.4. The Algorithm of FDTM

The proposed face detection algorithm is given as follows:

Step 1. The input image in the RGB format is converted into YCbCr color space and is used to segregate skin regions using a new linear decision boundary skin classification algorithm.

Step 2: The skin regions are segregated from non-skin regions with the help of YCbCr and YIQ color spaces.
Step 3. The input image in the RGB format is converted into YCbCr, HSV and YIQ color spaces. With the help of the new linear decision boundary skin classifier technique the skin region is segmented from the color image.

Step 4. The commonly used color spaces like, YCbCr, HSV and YIQ are combined to segment human skin regions in the color image.

Step 5. The commonly used color spaces like, normalized RGB, YCbCr, HSV, RGB and YIQ are combined to segment human skin regions in the color image.

Step 6. The template matching technique is used to verify the presence of a facial image in the color image given and the face is marked with a rectangle.

In FDTM, a new human skin detection technique is developed and implemented using images with different pose, illumination conditions. This algorithm gives very good results for images with controlled lighting conditions. Experiments with variety of images proved that this technique of detecting face images is more efficient and useful. The method is good because it reduces much of the computational work. This approach works well with the general techniques using the aspect ratio. But when the same technique is used with template matching technique it produces better results. The images have different lighting conditions, background clutter in the image, multiple faces in the image, as well as variations in face position, scale, pose and expression. The segmentation performance is measured in terms of the correct detection rate (CDR). The CDR is the percentage of skin pixels correctly classified.