Egyptian Computer Science Journal ,ECS ,Vol. 36 No. 1, January 2012 ISSN-1110-2586

# Faces and Eyes Detection Based on HSL and Red Colour Components and SVM in Facial Images

**Mohamed A. Berbar**
Department of Computer Engineering and Science, Menoufia University, Egypt
m_berbar@hotmail.com

## Abstract

The first step in many faces detection techniques is skin colour detection. In this paper, many skin colour detection techniques are investigated and compared with a new proposed technique for skin detection using HSL and Red colour components. The databases used for testing is the Caltech, Freet and MUCT colour image databases. The testing results proved that the proposed skin detection technique is the best among techniques in the literature using all types of images from the three databases even that suffer from colour constancy or different lighting conditions. SVM also is used as classifier for skin pixels using HSL and Red as features vector to automate the classification process. The proposed Facial features like eyes are detected also.

**Keywords** : Colour spaces, faces detection, skin-colour modelling, skin colour detection, facial features detection, SVM.

## 1. Introduction

The ability of any skin-colour detection technique to be more invariant to the changes in the lighting and the viewing environment is considered as a very important factor for its success. Illumination variation is the most important problem because it seriously degrades the accuracy. The ability of the human's eye to reduce the effect of light on the colour of the object and to retain a stable perceptual representation of the surface colour is referred to as chromatic adaptation or colour constancy [1-5]. The second problem is that human skin colour varies from person to another belonging to different ethnics. For example, the skin colour of people belonging to Caucasian, African, Asian and Arabian groups is different from one another and ranges from white, yellow to dark. Several computer vision algorithms have been developed for skin colour detection. The skin detector typically transforms a given pixel into an appropriate colour space and then uses a skin classifier to label the pixel whether it is a skin or a non-skin pixel. A skin classifier defines a decision boundary of the skin colour class in the colour space based on certain rules. Skin detection technique based on colour modeling has gained high popularity because of its fast processing. Also, many experts claim that human skin has a specific colour, and can be easily recognized. So using skin colour modelling approaches for skin detection is a good trend proposed by skin colour properties and common sense. The choice of the appropriate colour space is crucial to model and classify skin-colour properly. Colour is represented in mixture of three coloured channels (red, green and blue). It is one of the most widely used colour space in computer sciences for the processing and storage of digital image data. The high correlation between channels, mixing of luminance and chrominance data make many researchers claim that it is not easy to decide which skin colour model to use. The researchers do not agreed on certain choice of colour model. Sebe et all. [8] claim that clusters in normalized RGB to be an appropriate model for skin-colour. The HS* colour spaces are known to be more resistant to illumination change. This property is helpful in the process of skin detection and that is why they are often used to detect skin colour [9, 27, 28, 31, 32]. Orthogonal colour spaces like YCbCr, YCgCr, YIQ, YUV may be forming as independent components as possible. YCbCr is one of the most popular approaches for skin-detection and used by many researchers [10-13, 21, 33]. The aim of this paper is to provide a novel skin colour detection technique that is applicable for still images or single frame and invariant if applicable to illumination variation and unbalanced colours. The remainder of the paper is organized as follows: Section 2 presents the used databases in this research. Section 3 focuses on related work in skin colour and faces detection techniques. Section 4 explains the complete proposed faces and eyes detection methodology. Section 5 emphasizes on evaluation of nine skin colour detection techniques and the proposed technique using HSL and Red. Section 6 discusses the results of using SVM as classifier for skin pixels using HSL and Red as features vector to automate the classification process. Section 7 discusses the results of eyes detection.

## 2. Faces Images Databases

The image databases used in this study were from three different databases. The first database is the Caltech image database which most of the subjects are Caucasian. All the images are frontal faces. The source of data set is the web site of California Institute of Technology. The set contains 450 face images, 896 x 592 pixels in Jpeg format, 27 or so unique people under with different lighting and unconstrained backgrounds. Figure 1 shows some samples of Caltech database images.

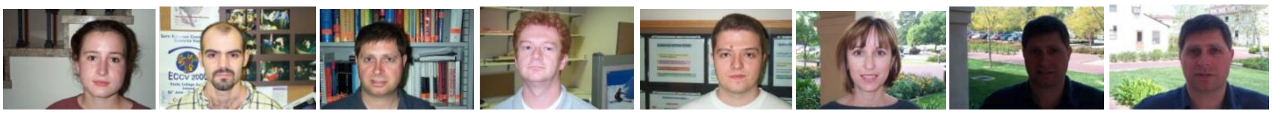


**Figure 1: Images from Caltech Image Database [18] with unconstrained background.**

The second dataset was the MUCT image database which has different races of subjects and suffer from different illuminations. The images that shown in Figure 2 for subjects who have agreed to allow their faces to be reproduced in academic papers. Each subject as explained in [16] was photographed with five webcams (a, b, c, d, and e) arranged yielding different views. The cameras were Unibrain Fire-i webcams with Sony ICX098BQ CCD sensors. Using ten different lighting setups (q, r, s, t, u, v, w, x, y , and z), each subject was photographed with two or three of these lighting sets. The name of the image convey the image number, lighting setups, camera view, gender, ... etc. The main problem with these images is the illumination reflection (IRP) from the face surface affects the skin colour appearance to be detected. The IRP is shown in images i000sd-fn, i002sa-mn, i000sa-fn, and i000se-fn.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| i000sd-fn | i002sa-mn | i002qb-mn | i200vb-mg | i000sa-fn | i000se-fn | i000qa-fn | i400wb-mn | i401wb-fn | i201tb-mg |

**Figure 2: Input samples of images from MUCT Database [16] have illumination reflection problem and with different lighting conditions.**

The 3rd database was Freet database of facial images collected under the FERET program, sponsored by the DOD Counterdrug Technology Development Program Office [14, 15]. Figure 3 shows some samples of Freet database.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 740_941201_fa | 740_941201_hl | 741_941201_hl | 742_941201_fb | 742_941201_rc | 743_960620_fb | 743_941201_hl | 744_941201_ql | 745_941201_rc | 746_941205_fb |

**Figure 3: Input samples of images from FERET Database [14, 15] have different lightings conditions.**

## 3. Related Work of Skin Colour Detection Techniques

In the this section, some popular skin colour detection techniques are explained and investigated to get the best one to use. Some researchers used genetic algorithm to find the best colour model to use like [29], and they conclude that HSI is the best method to use in skin segmentation using multiple thresholding. What I am going to do is to confirm his conclusion or find better solution.

### 3.1. RGB Colour Model

This RGB colour space was used by some researchers [23-26]. The following simple explicit skin colour detection technique which proposed by Peer et al. [26] was implemented and investigated to be compared to other techniques [11, 12, 17, 20, 26, 28, 30, 31].

R, G, B) is classified as skin if:

$$(R > 95) \text{ AND } (G > 40) \text{ AND } (B > 20) \text{ AND } (\max(R, G, B) - \min(R, G, B) > 15) \text{ AND } (|R - G| > 15) \text{ AND } (R > G) \text{ AND } (R > B) \quad (1)$$

In case of flashlight or daylight lateral illumination:

(R, G, B) is classified as skin if:

$$R > 220 \text{ AND } G > 210 \text{ AND } B > 170 \text{ AND}$$

$$|R - G| <= 15 \text{ AND } B < R \text{ AND } B < G. \quad (2)$$

Where R, G, B are the colour components Red, Green, and Blue ranging [0 .. 255].

### 3.2 Normalized RGB (r, g, b) Colour Model

Many researchers used normalized RGB [35-39], they assumed that Norm RGB is the most effective to extract a skin locus successfully. This is because it is as little as possible dependent on the illuminant [39]. The following normalized RGB formulas proposed by Gomez and Morales [31] are implemented

$$\frac{r}{g} > 1.185, \quad \frac{r.b}{(r+g+b)^2} > 0.107 \text{ and } \frac{r.g}{(r+g+b)^2} > 0.112 \quad (3)$$

Where *rgb* are the normalized coordinates obtained as:

$$r = \frac{R}{(R+G+B)}, g = \frac{G}{(R+G+B)}, b = \frac{B}{(R+G+B)}$$

### 3.3. YCbCr Colour Model

The named orthogonal colour spaces can be obtained from a linear or non-linear transformation from RGB. The colour space channels represent the colour with statistically independent components (as independent as possible). The YCbCr space is an encoded nonlinear RGB signal. The simplicity of transformation and explicit separation of chrominance and luminance components makes this colour space attractive for skin colour modelling [7, 11, 12, 33, 34]. The Y component contains the luminance information; and, the chrominance information is found in the chrominance blue Cb and in the chrominance red Cr. The RGB components have been converted to the YCbCr components using the following formula [34].

$$\begin{aligned} Y &= 0.257 * R + 0.504 * G + 0.098 * B + 16 \\ Cb &= -0.148 * R - 0.291 * G + 0.439 * B + 128 \\ Cr &= 0.439 * R - 0.368 * G - 0.071 * B + 128 \end{aligned} \quad (4)$$

The Y component has 220 levels ranging from 16 to 235; Cr Cb components have 225 levels ranging from 16 to 240. In the skin colours detection process, each pixel was classified as skin or non-skin based on its colour components. Although, different people have different skin colours but there is a range of values for skin colour according to experimental results. The corresponding skin cluster is given by Chai and Ngan [11] is shown in Equation 5:

$$77 <= Cb[i,j] <= 127 \text{ AND } 133 <= Cr[i,j] <= 173 \quad (5)$$

and proposed also by Kukharef and Novosielsky [12] Equation 6:

$$Y[i,j] > 80 \text{ AND } 85 < Cb[i,j] < 135 \text{ AND } 135 < Cr[i,j] < 180 \quad (6)$$

and also by Berbar et al. [33] in Equation 7.

$$\begin{aligned} &85 < Cb[i,j] < 127 \text{ AND} \\ &137 < Cr[i,j] < 177 \text{ AND} \\ &183 < (Cb[i,j] + 0.6\, Cr[i,j]) < 219 \end{aligned} \quad (7)$$

Where Y, Cb, Cr = [0,255]

The skin detection techniques proposed by [11, 12] were implemented and investigated to be compared with other techniques [17, 20, 26, 28, 30, 31].

### 3.4. HS* (HSI – HSL – HSV) Colour Models

Colour spaces models based on Hue (H) and Saturation (S) describe colour based on the artist's idea of tint, saturation and tone. Hue defines the dominant colour (such as red, green, purple and yellow) of an area; saturation measures the colourfulness of an area in proportion to its brightness. The space "intensity (I)", "lightness (L)" or "value (V)" is related to the colour luminance. The intuitiveness of the colours space components and explicit discrimination between luminance and chrominance properties made these colour spaces popular in the works on skin colour segmentation [40-46]. Several interesting properties of Hue were noted in [6, 13]. It is invariant to highlights at white light sources, based on intuitive values and also, can be transferred to 2D by removing the illumination component. Skin-colour pixels of Saturation component have wider distribution than hue component [22]. That assumption because off saturation defines the relative purity or the amount of white light mixed with a hue that is a colour attribute as a pure colour. Because hue and saturation colour model is the most immune to light variations, it has been used by many researchers [27- 32].

Lin [31] proposed an HSL colour model as follow:

If (L[i, j] > 40) AND H[i, j] < 28 ) OR (H[i, j] > 332) AND S[i,j] = [13:110]) OR
H[i, j] = [309:331]) AND S[i, j] = [13:75] (8)
Then pixel at [i, j] is skin

Where H, S are the colour components Hue and saturation and ranging [0...360], and [0…255] respectively.

When testing Lin's technique [31], the results were not quite acceptable. The results dramatically enhanced when proposing a modification by removing the condition (S [i, j] < 110) from that test. That may be because many images under processing are affected with different lightings which has great effect on colour saturation as will be explained later in this paper. Kannumuri and Rajagopalan [32] proposed a skin colour detection model using hue and saturation components as follows:

If (colour histogram (H, S) > 0.1)
then skin (i, j) = 1 i.e. (i, j) is a skin pixel
else skin (i, j) = 0 i.e. (i, j) is a non-skin pixel (9)

Oliveira, and Conci [28] proposed a skin colour detection model using hue component as follows:

If ((H[i, j] > 6) AND ( H[i, j] < 36) (10)
then the [i, j] is a skin pixel

The skin detection techniques proposed by [31, 32] are implemented and compared with other techniques [11,12, 17, 20,26, 28].

### 3.5. Hybrid Colour Models Techniques

There is no single colour model that works best for all kinds of images, some researchers like [22, 17] thought that using hybrid colour model will give better results than using one colour model and will be suitable for skin pixel classification under different conditions, i.e. different races and varying illuminations. Sawangsri et al [20] used colour information of Hue and Cr to define skin-colour and estimate a reference map in YCbCr and HSV colour space. Moreover, $R_{Cr}$, $R_{Cb}$ , $R_H$ , and $R_S$ is denoted as the respective ranges of Cr, Cb, Hue, and saturation values that correspond to skin-colour. Sawangsri et al [20] used the following ranges.

$R_{Cr}$ = [133: 173], $R_{Cb}$ = [77:127] from [11] AND
$R_H$ = [0: 50] $R_S$= [0.23: 0.68] [21]. (11)

Rahman et al.[17] used three rules to decide is the candidate pixel is skin or not. The first rule Rule1 = equation (1) OR equation (2) using RGB model [26], the second and third rules are as follow:

Rule2 = ($Cr \le 1.5862 \times Cb + 20$) AND ($Cr \ge 0.3448 \times Cb + 76.2069$) AND ($Cr \ge -4.5652 \times Cb + 234.5652$) AND ($Cr \le -1.15 \times Cb + 301.75$) AND $Cr \le -2.2857 \times Cb + 432.85$
Rule3 = Hue [i, j] < 25 OR Hue [i, j] > 230 (12)

If Rule1 OR Rule2 OR Rule3 then the pixel at [i, j] is in skin colour.

When implementing and investigating this technique, I was surprised with the results as Rule2 is the cause of passing most of the false skin pixels when testing it with test images from Caltech Image Database [18].

## 4. The complete proposed Face and Eyes Detection System

The complete system to extract faces and facial features is shown in figure 4. The first step is applying the proposed skin colour detection technique to detect skin colour then combining the edges image with the resulted image of skin colour detection. Region labelling function is used to isolate and identify the location of the expected face. The isolated face should satisfy some features like size and height to width ratio. The red colour component is separated from the original colour image and the face area is isolated from red colour component also using the information of its location from previous stage. The extracted colour image of the face is thresholded and also the extracted face from red colour component. Then applying logic OR operation between both the resulted two images from thresholding. That step is useful for good extraction of the eyes and eliminates the other facial features. For exact extraction of the center of the eye, the following steps are implemented. Vertical histogram is applied on the grey scale image of the eye as shown in figure 5. The x-dimension of maximum value is considered as $x_{center}$ of the eye. The $y_{center}$ of the eye is calculated using circle fitting function.

### 4.1. The Proposed Skin Detection Technique Based on HSL and R Colour Components

The high correlation between channels, mixing of luminance and chrominance data make many researchers claim that this is the cause why RGB is not a suitable choice for colour analysis and colour-based recognition techniques. In this paper, we say that this claim is not completely right. Our claim is that all channels of colour models affected by luminance. Our claim rely on the logic sense that most of the other colour spaces are calculated from the mixed luminance and chrominance RGB so in some way theses colour spaces chrominance components also affected by luminance. Because of that discussion, my proposal is to use hybrid colour model to classify skin colour pixels. The used eight components were hue (H), saturation (S), lightness (L), red (R), green (G), blue (B), cyan (C), and magenta (M). Using histogram based approach to find the skin colour range in every colour component. I got eight ranges for the eight colour components. Then, the skin classification process is simplified by removing one range by one and testing to see if the result is affected or not. This process is applied over a selected subset of the Caltech dataset [18]. The selected subset faces images are from different types of faces images with different lightings and backgrounds. From experimental testing, the remaining effective conditions were four ranges for hue (H), saturation (S), lightness (L), and red (R) components which are sufficient to classify the skin colour. My expectation for successful components as hue and saturation because of their interesting properties [6, 13] and most resistance to light variations in the images of the dataset, and the red component because it has a considerable contribution in skin colour. Light component is taken because of its effect on stability on skin colour model. The experimental results produce the following hybrid model by investigating the histogram of the mentioned colour component of skin and none skin pixels.

T1 = H[i, j] < 24 AND R[i, j] > 125 AND S[i, j] > 20 AND L[i, j] > 80
T2 = H[i, j] >185 AND R[i, j] > 155 AND S[i, j] > 20 AND L[i, j] > 114 (13)
T3 = = H[i,j] < 36 AND R[i, j] > 85 AND L[i, j] > 60 AND S[i,j] > 40
If (T1 OR T2 OR T3) then Pixel at [i, j] is skin.

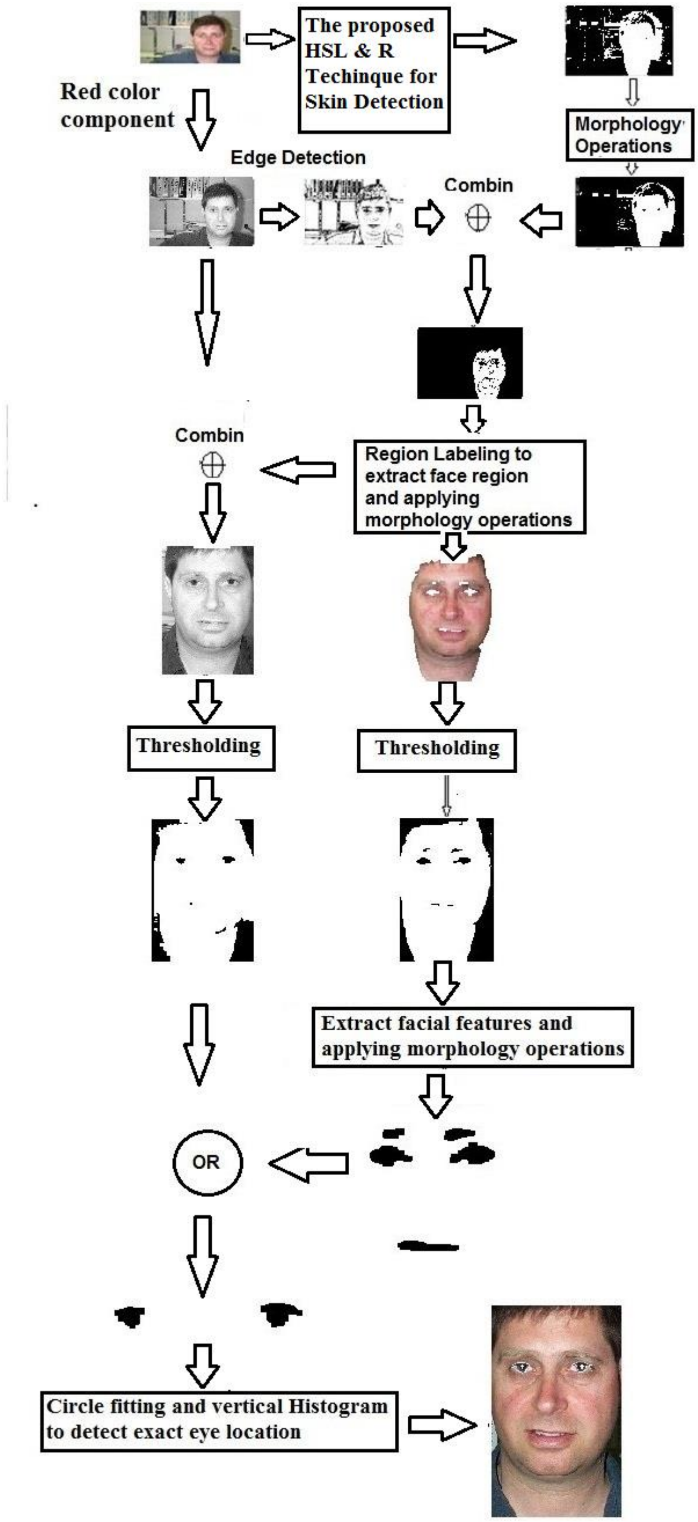



**Figure 4: The complete system to extract faces and Eyes.**

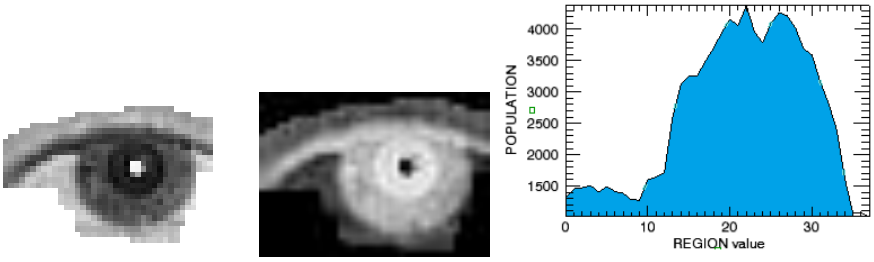



**Figure 5: Red component image of extracted eye and its negative image and its vertical histogram.**

## 5. Evaluation of Skin Colour Detection Techniques

This section discusses the results of different skin detection techniques using three databases, MUCT database [16], database [14, 15 ] and  Caltech database [18].  Five different metrics [19] are used to evaluate the results of the skin detection techniques and to determine which technique yields the best skin detection results. The accuracy ACC% is the percentage rate of skin and non skin pixels correctly classified. The False Acceptance Rate (FAR %) is the percentage of non skin pixels which the technique considered them as skin pixels. The False Rejection Rate (FRR %) is the percentage of skin pixels which the technique reject them wrongly as non skin pixels. The accuracy (ACC), FAR, and FRR are expressed in Equations 14: 16.

$$Accuracy\ (CCR\%) = \frac{number\ of\ pixels\ correctly\ classified}{Total\ test\ pixels} \qquad (14)$$

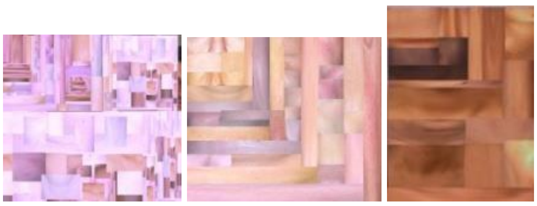
$$FAR\ \% = \frac{Number\ of\ non\ skin\ pixels\ wrongly\ classified}{Total\ test\ pixels} \qquad (15)$$

$$\mathrm{FRR\%} = \frac{Number\ of\ skin\ pixels\ wrongly\ classified}{Total\ test\ pixels} \qquad (16)$$

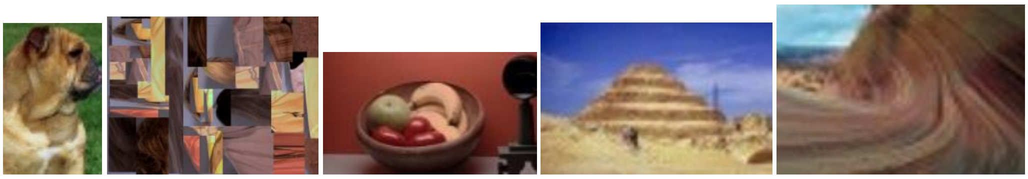
Next, subsection 5.1 discusses the results when the images not suffer from colour constancy problem, subsection 5.2 discuss the results of images suffer from colour constancy.

### 5.1. Evaluation of Skin Colour Detection Techniques for Images without Colour Constancy.

The first set of images were consists of collection of skin samples collected from Caltech image database which has Caucasian subjects, and samples of images were consists of collection of confusing non-skin samples. The second set were consists images of collection of skin samples collected from MUCT and Caltech image databases which has different races and suffer from different illumination and also some images contain confusing non-skin pixels. The samples are shown in Figure 6.



(a)  Skin samples



(b) non skin samples

**Figure 6: Samples of testing images to evaluate skin colour detection techniques.**

### 5.1.1 Techniques Evaluation using Caltech Image Database

Nine skin detection techniques and the proposed one are investigated also on the images from the Caltech Image Database [18]. The dataset contains 450 face images, 896 x 592 pixels in Jpeg format with different lighting, expressions, and backgrounds. Table 1 shows the results of applying evaluation metrics used for evaluation. Figure 7 shows the output of skin colour detection techniques using testing images collected from Caltech image database [18]. From the results shown in Figure 7 and Table 1, the best techniques which have accuracy greater than 80 % were techniques [26], [12], and the proposed one. The results of these techniques are acceptable compared to other techniques.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| [26] | [31] | [11] | 12] | [30] | [20] | [28] | [32] | [33] | Proposed |

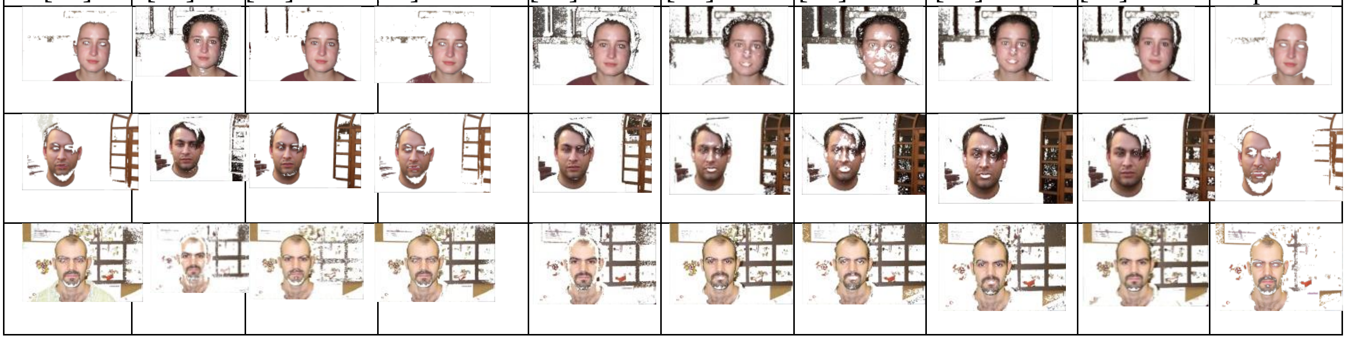


**Figure 7: (a) Output of some skin colour detection techniques using samples shown in Figure 1.**

**Figure 7: (b) Faces Extraction after removing background.**

| TABLE 1: Comparison of ten skin detection algorithms<br>Total pixels were 6,484,771, Skin pixels were 3,158,528, and non skin pixels were 3,326,243 | | | |
|---|---|---|---|
| Ref. number | Accuracy (ACC%) | False Acceptance Rate (FAR %) | False Rejection Rate (FRR %) |
| [26] | 86.7 | 3.80 | 9.52 |
| [31] | 68.7 | 0.57 | 30.7 |
| [11] | 83.2 | 2.32 | 14.4 |
| [12] | 86.9 | 3.57 | 9.5 |
| [30] | 48.8 | 3.53 | 47.7 |
| [20] | 75.9 | 4.36 | 19.3 |
| [28] | 69.5 | 4.36 | 26.1 |
| [32] | 77.1 | 3.64 | 19.3 |
| [17] | 65.8 | 25.1 | 9.14 |
| Proposed | 88.4 | 2.86 | 8.68 |

### 5.1.2 Techniques Evaluation using MUCT Database

Nine skin detection techniques and the proposed one are investigated on the images from the dataset which not suffer from colour constancy or illumination reflection problem to decide which technique is the best for the MUCT image database under processing. Table 2 shows the results of applying metrics used for evaluation. The best technique which has the best accuracy was the proposed one.

| TABLE 2 : Comparison of Ten skin detection algorithms<br>Total pixels were 5,244,221, Skin pixels were 2,931,087, and non skin pixels were 2,313,134 | | | |
|---|---|---|---|
| Ref. number | Accuracy (ACC%) | False Acceptance Rate (FAR %) | False Rejection Rate (FRR %) |
| [26] | 73.5 | 3.82 | 22.6 |
| [31] | 66.6 | 4.36 | 29.0 |
| [11] | 70.7 | 0.97 | 28.2 |
| [12] | 72.7 | 4.89 | 22.3 |
| [30] | 70.7 | 1.82 | 27.4 |
| [20] | 69.1 | 0.98 | 29.9 |
| [28] | 75.6 | 2.81 | 21.5 |
| [32] | 69.8 | 1.22 | 28.9 |
| [17] | 53.9 | 0.67 | 45.3 |
| Proposed | 79.5 | 8.65 | 11.8 |

The algorithm by Rahman et.al. 2006 [17] is excluded from the comparison because of its low accuracy. When working on images from MUCT database, I noticed that the images with lighting conditions (s, and v) suffer from illumination reflection from the face surfice which greatly affect the skin detection operation so I used the IRPS approach [1] to reduce illumination reflection problem. The results of ten techinques in the leteature including the proposed techinque of skin colour detection are shown in Figure 8.

**Fig. 8: (a) Samples of testing images from MUCT Image Database to evaluate skin colour detection techniques**

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| [26] | [31] | [11] | [12] | [30] | [20] | [28] | [32] | [33] | Proposed |

**Figure 8: (b) Results of ten skin colour detection techniques.**

From the results shown in Figure 8 and Table 2, the best technique which has greater accuracy is the proposed one.

### 5.1.3 Techniques Evaluation using Freet Database

Figure 9 shows the output of skin colour detection techniques using testing images collected from Freet image database [14, 15]. From the results shown in Figure 9, the best results observed are from the proposed technique.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| [26] | [31] | [11] | [12] | [30] | [20] | [28] | [32] | [33] | Proposed |

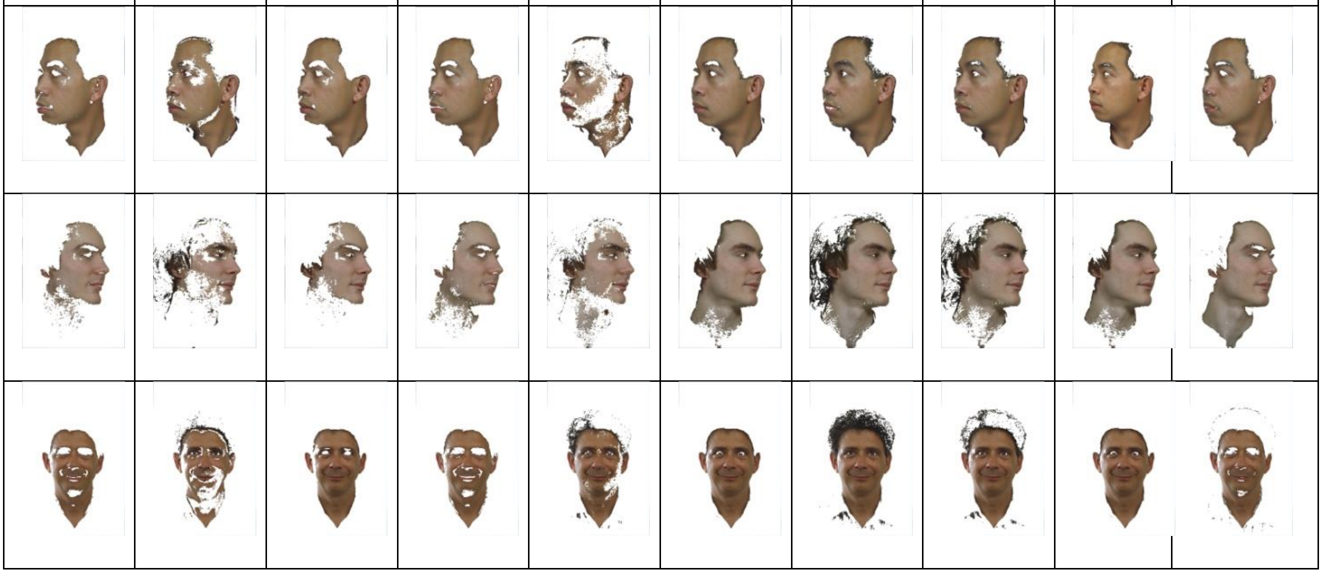


**Figure 9: Output of some skin colour detection techniques using Freet Database samples shown in Figure 3.**

### 5.2. Skin Colour Detection Results of Images with Colour Constancy Problem.

The used test images were from Caltech Image Database [18]. About 45 images with colour constancy problem were collected from the dataset to test the colour correction approaches under investigation. The tested colour images have excessive redness or blueness. Skin samples are gathered from the 45 unbalanced images and these images are not equally affected by colour constancy problem. Figure 10 shows some of the samples.

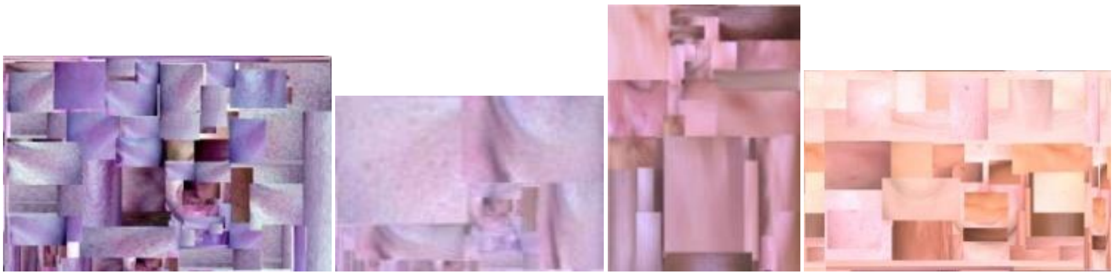


**Figure 10: Samples of skin areas affected by colour constancy problem.**

Table 3 shows the calculated evaluation metrics resulted from applying the skin colour detection techniques without applying colour correction. The accuracy of all the techniques are less than 65% except the proposed technique which proved to be most resistance to colour constancy problem. The accuracy of the proposed technique is 80.23%. From the demonstrated results shown in Table 3, the proposed skin colour detection techniques proved its reliability and robustness, it is the best among all investigated skin colour detection techniques and of course it will be the best when testing the investigated techniques with images with colour constancy problem after applying colour correction explained in [1].

TABLE 3 :Comparison of ten skin detection algorithms
Total pixels were 4004562. Skin pixels were 1085448, and non skin pixels were 2919114. The rates before doing correction.

| Ref. number | Accuracy (ACC%) | False Acceptance Rate (FAR %) | False Rejection Rate (FRR %) |
|---|---|---|---|
| [26] | 63.79 | 2.4 | 33.81 |
| [31] | 63.67 | 0.6 | 35.72 |
| [11] | 63.02 | 1.1 | 35.79 |
| [12] | 63.67 | 1.51 | 34.81 |
| [30] | 62.41 | 2.65 | 34.9 |
| [20] | 62.64 | 1.41 | 35.94 |
| [28] | 62.56 | 1.47 | 35.96 |
| [32] | 62.80 | 1.24 | 35.95 |
| [17] | 49.37 | 15.6 | 34.98 |
| Proposed | 80.23 | 5.23 | 14.54 |

## 6. The Proposed Skin Detection technique using SVM

The proposed model is using thresholds which were determined by investigating the histogram of the successful skin colour features or components Hue, Saturation, Lightness, and Red heuristically. The aim here is to automate the process of skin colour separation using SVM to get better separation accuracy.

Support Vector Machine (SVM) is part of a group of kernel based methods which are used for pattern classification. A classifier takes an input pattern called feature vector which have the values of Hue, Saturation, Lightness, and Red , and determines to which class it belongs to.

Let $y_i$ , $i$ =1, 2, 3, 4 be feature vectors of a training set Y, which belong to either of two classes skin, non-skin. Using this training data, SVM finds an optimal hyper plane with maximum margin that separates the unknown input pixels into 2 classes as shown in Figure 11. Many hyperplanes separating the feature vectors are possible; SVM finds the one that has maximum margin and better generalization accuracy for classification. The accuracy of an SVM classifier is dependent on the choice of a proper kernel function.

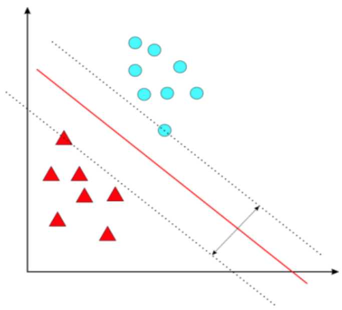


**Figure 11: SVM classifies by finding the optimal hyperplane that has maximum margin.**

About 564816 of skin and none-skin pixels which are shown in Figure 12 were used for training and testing a SVM classifier to isolate skin pixels from non-skin pixels. Half of the pixels set are randomly selected for testing and the other half of pixels were used for testing. It is known that accuracy of SVM is greatly affected by the choice of a kernel function among other factors. The RBF kernel is a reasonable first choice because of it has fewer numerical difficulties [47, 48]. This kernel nonlinearly maps samples into a higher dimensional space so it, unlike the linear kernel, can handle the case when the relation between class labels and attributes is nonlinear.

Radial basis function kernel is given as:

$$K(x_i + x_j) = e^{\left(-\gamma \|x_i + x_j\|^2\right)} \qquad where \;\; \gamma > 0$$

Use cross-validation to find the best parameter C and $\gamma$. C > 0 is the penalty parameter of the error term.

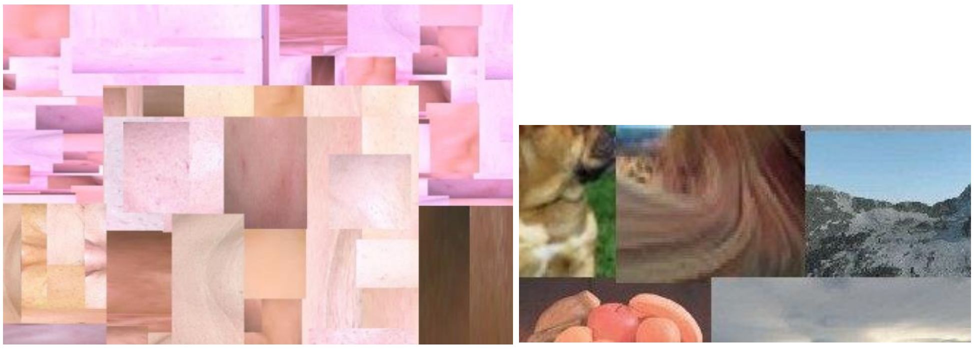


**Figure 12: Skin and non-Skin pixels used for training and testing a SVM classifier.**

Many values of C and $\boldsymbol{\gamma}$ have been tested and specificity, sensitivity, and accuracy are calculated. The best results are shown in Table 4 compared to the proposed technique which uses thresholding.

| Table 4 | Performance | Accuracy | Specificity | Sensitivity | $\log_2 \gamma$ | $\log_2 c$ |
|---|---|---|---|---|---|---|
| SVM | 95 | 97.35 | 92.27 | 97.81 | -17 | 17 |
| Proposed | 78.03 | 92.27 | 61 | 95 | -- | -- |

Where specificity, sensitivity and performance is defined as:

$$\text{Sensitivity} = \frac{Number\ of\ skin\ pixels\ correctly\ classified}{Number\ of\ skin\ pixels} \qquad (17)$$

$$\text{Specificity} = \frac{Number\ of\ non\ skin\ pixels\ correctly\ classified}{Number\ of\ non\ skin\ pixels} \qquad (18)$$

$$\text{Performance} = 0.5 \times (Sensitivity + Specificity) \qquad (19)$$

From results of table 3, it is clear the improvement of the accuracy rate of the proposed technique for skin colour detection with heuristic thresholding.

## 7. Eyes Detection Results

After skin colour detection, it will be easier to detect faces and detecting facial features like eyes and mouse even the focus here is detecting eyes. The proposed technique successfully detect the face and its features even though it is suffering from excessive blueness as shown in first image shown in Figure 13, and also for the second image which has a difficult background and the third image which have dark face and light background. Figure 14-16 show more results of eyes detection using the proposed methodology on images samples from the three databases.

**Figure 13: Results of applied methodology on samples of difficult images.**

**Figure 14: Eyes Detection Results of applied methodology on samples of Caltech database.**

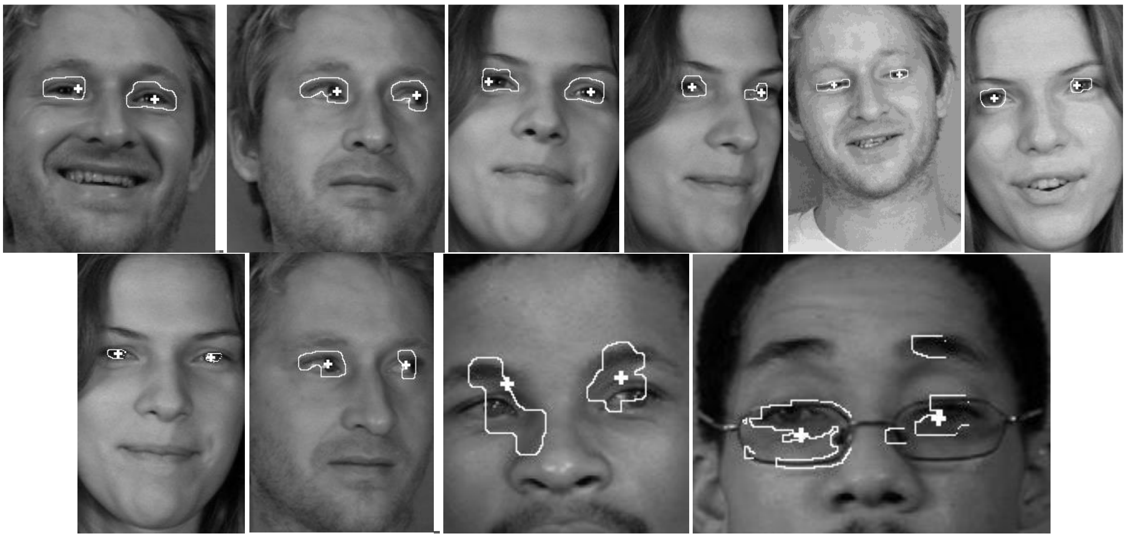


**Figure 15: Eyes Detection Results of applied methodology on samples of MUCT database.**

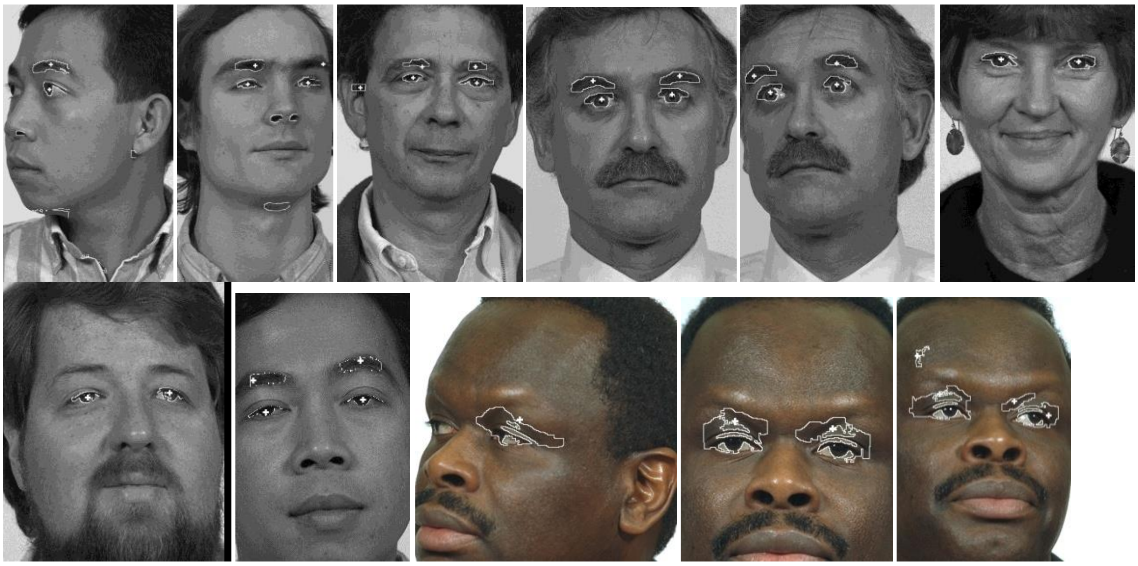


**Figure 16: Eyes Detection Results of applied methodology on samples of Freet database.**

It is clear that the detection of eyes is granted using the proposed method of eye detection as long as the faces extracted or even the upper part of it is extracted. The problem to extract the location of eye accurately is faced with black people and those who are wearing glasses and also in most of subjects of MUCT database bad lightings. Of course I also faced a problem in detecting both eyes when the subject looking side view.

## 8. Conclusion

The results of skin detection techniques are enhanced much more when applying the approach explained in [1] for colour correction prior to skin colour detection on images with colour constancy problem. Nine of the skin colour detection techniques are investigated. New hybrid technique using HSL and RGB colour models to detect skin colour is proposed. The overall accuracy of the proposed skin colour detection technique is greater than the overall accuracy of nine techniques in the literature when testing Caltech dataset images and MUCT database. The comparison of the proposed technique for skin colour detection with other techniques proved its reliability and robustness and to be the best among them especially with colour constancy problem. SVM also is used as classifier for skin pixels using HSL and Red as features vector to automate the classification process and improves the accuracy rate of the proposed technique for skin colour detection. Faces and facial features are detected but it may need more research work to detect more accurately other facial features like mouse especially when subject with moustache and beard.

## References

[1] M. A. Berbar, "Novel Colours Correction Approaches for Natural Scenes and Skin Detection Techniques", The International Journal of Video & Image Processing and Network Security (IJVIPNS),ISSN:2077-1207, Volume 11 Issue 02, pp.1-10, 2011.

[2] K. Barnard, L. Martin, A. Coath, and B. Funt. A Comparison of Computational Colour Constancy algorithms-Part 2: Experiments with Image Data. IEEE Trans. Image Processing, Vol. 11, No. 9, pp: 985-996, 2002.

[3] D. Forsyth. A novel algorithm for colour constancy, International Journal of Computer Vision, vol. 5, pp: 5-36, 1990.

[4] E. H. Land, The Retinex theory of colour vision . Scientific American,vol.237,pp: 108-129, 1977.

[5] V. Cardei, A neural network approach to colour constancy. PhD thesis, Simon Fraser Univ., Burnaby, BC, Canada, 2000.

[6] P. Kakumanu, S. Makrogiannis, N. Bourbakis, "A survey of skin-colour modeling and detection methods", Pattern Recognition 40, pp: 1106–1122, 2007.

[7] C. Liensberger, J. Stöttinger, M. Kampel, Colour-Based and Context-Aware Skin Detection for Online Video Annotation, MMSP’09, Proceedings of the IEEE International Workshop on Multimedia Signal Processing, Rio de Janeiro, Brazil, 2009

[8] N. Sebe, I. Cohen, T. S. Huang, and T. Gevers, “Skin detection: A bayesian network approach,” in ICPR, pp: 903–906, 2004.

[9] Z. Fu, J. Yang, W. Hu, and T. Tan, Mixture clustering using multidimensional histograms for skin detection, in ICPR, 2004, pp: 549–552.

[10] R.L. Hsu, M. Abdel-Mottaleb, A.K. Jain, Face detection in colour images, IEEE Trans. Pattern Anal. Machine Intell. 24 (5), pp: 696–706, 2002.

[11] D. Chai, K.N. Nygan, Locating facial region of a head-and-shoulders colour image, ICFGR98, Proceedings of the 3rd. International Conference on Face & Gesture Recognition, pp: 124-129,1998.

[12] G. Kukharev, A. Novosielski, Visitor identification elaborating real time face recognition system, In Proc. 12th Winter School on Computer Graphics (WSCG), Plzen, Czech Republic, pp:157-164, 2004.

[13] V. Vezhnevets, V. Sazonov, A. Andreeva, A survey on pixel-based skin colour detection techniques, GRAPHICON03 (CCGV), pp: 85-92, 2003.

[14] P.J. Phillips, H. Wechsler, J. Huang, P. Rauss,"The FERET database and evaluation procedure for face recognition algorithms,"Image and Vision Computing J, Vol. 16, No. 5, pp. 295-306, 1998.

[15] P.J. Phillips, H. Moon, S.A. Rizvi, P.J. Rauss,"The FERET Evaluation Methodology for Face Recognition Algorithms,IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 22, pp. 1090-1104, 2000.

[16] Milborrow and J. Morkel and F. Nicolls, The MUCT Landmarked Face Database, Journal of Pattern Recognition Association of South Africa, 2010,http://www.milbo.org/muct

[17] N. A. Rahman, Kit C. Wei, John See, 'RGB-H-CbCr Skin Colour Model for Human Face Detection, In Proceedings of The MMU International Symposium on Information & Communications Technologies (M2USIC 2006).

[18] http://www.vision.caltech.edu/html-files/archive.html

[19] C. A. Doukim, J. A. Dargham, and A. Chekima, Comparison of three colour spaces in skin detection, Borneo Science 24, pp: 75-81, 2009.

[20] T. Sawangsri, V. Patanavijit, and S. Jitapunkul, Face Segmentation Using Novel Skin-Colour Map And MorphologicalTechnique, In Proceedings of World Academy of Science, Engineering and Technology, V2, pp: 41-44, 2005.

[21] K. Sobottka, I. Pitas, Extraction of facial regions and features using colour and shape information, ICPR96, 1996.

[22] J. Choi, S. Lee, C. Lee and J. Yi, A Real- Time Face Recognition Systems Using Multiple Mean Faces And Dual Mode Fisher faces, IEEE Symposium on Industrial Electronics, Vol.3, pp:1686-1689, 2001.

[23] J. Brand, J. Mason, A comparative assessment of three approaches to pixel level human skin-detection. In Proc. of the International Conference on Pattern Recognition,vol.1, pp, 1056–1059, 2000.

[24] M Jones, J. M. Rehg, Statistical colour models with application to skin detection. InProc.oftheCVPR'99,vol.1, pp: 274–280, 1999.

[25] M. J. Jones and J. M. Rehg, "Statistical colour models with application to skin detection." IJCV, vol. 46, no. 1, pp: 81–96, 2002.

[26] P. Peer, J. Kovac, F. Solina, "Human Skin Colour Clustering for Face Detection", EUROCON1993, Ljubljana, Slovenia, pp: 144-148, September 2003.

[27] A. Conci, E Nunes, J. J. Pantrigo, A. Sanchez, "Comparing colour and texture-based algorithms for human skin detection", vol. 5, Computer Interaction pp:168-173, 2008.

[28] V. Oliveira, A. Conci (UFF), Skin detection using HSV colour space -SIBGRAPI - XXIInd Brazilian Symposium on Computer Graphics and Image Processing, do Rio de Janeiro (PUC-Rio), 2009.

[29] F. Gasparini and R. Schettini, "Skin segmentation using multiple thresholding," in SPIE, vol. 6061, no. 1. SPIE, 2006.

[30] C. Lin "Face Detection, Pose Classification, and Face Recognition Based on Triangle Geometry and Colour Features" PhD theis by Chiunhsiun Lin, Advisor: Prof. Kuo-Chin Fan, in Institute of Computer Science and Information Engineering, National Central University, Chung-Li, Taiwan, 2001.

[31] G. Gomez and E.F. Morales, "Automatic feature construction and simple rule induction algorithm for skin detection, Proc. Of the ICML workshop on machine learning in Computer Vision. A. Sowmya, T. Zrimec (eds), 2002.

[32] S. Kannumuri and A.N. Rajagopalan, "Human Face Detection in Cluttered Colour Images Using Skin Colour and Edge Information", Indian Conference on Computer Vision, Graphics and Image Processing (ICVGIP'02), (Ahmedabad, India), 2002.

[33] M. A. Berbar, H. M. Kelash and A. A. Kandeel "Faces and Facial features Detection in Colour Images", GMAI06, London, UK, ISBN/ISSN: 0-7695-2604-7, IEEE Computer Society, pp: 160-168, 2006

[34] J.Yang, W.Lu, andA. Waibel,"Skin Colour modeling and Adaptation ", ACCV, pp: 687-694, 1998.

[35] J.A Dargham, A. Chekima, Lips Detection in the Normalised RGB Colour Scheme, Proceedings of the International Conference on Information and Communication, 2006.

[36] B.Martinkauppi. Face colour under varying illumination - analysis and applications, PhD thesis, University of Oulu, 2002.

[37] F. Tomaz, T. Candeias, and H. Shahbazkia. Improved automatic skin detection in colour images. In 7th Digital Image Computing: Techniques and Applications, pp: 419–427, 2003.

[38] T. Wilhelm, H. J. Bhme, and H. M. Gross. A multi-modal system for tracking and analyzing faces on a mobile robot. In Robotics and Autonomous Systems 48, pp: 31–40, 2004.

[39] Alvise Lastra, Alberto Pretto, Stefano Tonello and Emanuele Menegatti**,** "Robust colour-based skin detection for an interactive robot", Lecture Notes In Artificial Intelligence; Vol. 4733, Proceedings of the 10th Congress of the Italian Association for Artificial Intelligence: Artificial Intelligence and Human Oriented Computing, Rome, Italy, pp: 507 - 518 , 2007.

[40] B.D., Zarit, B.J., Super, and F.K.H. Quek, "Comparison of five colour models in skin pixel classification". In Int. Workshop on Recognition, Analysis, and Tracking of Faces and Gestures in Real-Time Systems, Corfu, Greece, Sept. pp: 58-63, 1999.

[41] S. McKenna, S. Gong, Y. Raja, Modeling facial colour and identity with Gaussian mixtures, Pattern Recognition 31 (12), pp: 1883–1892, 1998.

[42] L. Sigal, S. Sclaroff, V. Athitsos, Skin colour-based video segmentation under time varying illumination, IEEE Trans. Pattern Anal. Mach. Intell. 26 (6),2004.

[43] Birchfield, S. 1998. Elliptical head tracking using intensity gradients and colour histograms. In Proceedings ofCVPR'98, pp. 232–237, 1998.

[44] Jordao, L., Perrone, M., Costeira, J., and Santos-Victor, J.. Active face and feature tracking. In Proceedings of the 10th International Conferenceon Image Analysis and Processing, pp: 572–577, 1999.

[45] Q. Zhu, K.-T. Cheng, C.-T. Wu, Y.-L. Wu, Adaptive learning of an accurate skin-colour model, AFGR04, 2004.

[46] Brown D., Craw I., Lewthwaite J., A SOM based approach to skin detection with application in real time systems, BMVC01, 2001.

[47] BURGES, Christopher J. C., A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery, **2**(2), pp. 121–167 , 1998

[48] Chih-Wei Hsu, Chih-Chung Chang, and Chih-Jen Lin, " A Practical Guide to Support Vector Classification", http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf , Apr 15, 2010

**Biographies**

Dr M. A. Berbar received his B.Sc. from Faculty of Electronic Engineering at Menoufia University - Egypt and his M.Sc. from Computer Sciences and Engineering at Menoufia University and his PhD from UMIST and Manchester University - UK. Currently he is working for King Saud University, KSA.