International Journal of Advanced Computer Technology (IJACT)

ISSN:2319-7900

Comparative Study between Linear and Non-linear Skin Color Classifiers

Ghazali Osman[1], Mohd Nasir Ismail[2], Zulkfili Mohamed[3], Muhammad Suzuri Hitam[4]

[1,2,3]Universiti Teknologi MARA, Malaysia
[4]Universiti Malaysia Terengganu, Malaysia

Abstract: Skin color detection is a process to determine whether a desired pixel or a group of pixels belongs to skin or non-skin color. The presence of skin and non-skin can be determined by manipulating pixel color. Skin color detection is often used as pre-processing in face detection, hand tracking, people detection and other vision applications. The goal of skin color detection is to build a decision rule that will discriminate between skin and non-skin pixels. There are many methods have been proposed in literature. Some of methods are based on linear separator, and others based on non-linear separator to discriminate between skin and non-skin groups. The objective of this paper is to study the performance of skin classifiers between linear and non-linear skin color classifiers with eight color models in developing skin color distribution model. There are two method have been used in this paper; linear discriminant analysis (LDA) and neural network (NN). LDA is represented for linear classification while NN is represented non-linear classification methods. The experiment result showed that the CIE-Lab color model is the most suitable color model to be used in linear and non-linear classification method to develop skin color model. Meanwhile the LUX color model is the most unsuitable for developing skin color distribution model using both LDA and NN.

Keywords: skin color classifier; skin color detection; linear classification; non-linear classification; linear discriminant analysis; neural network; pixel-based classification;

I. INTRODUCTION

Skin color is produced by combination of melanin, carotene, bilirubin, and hemoglobin. Skin color can be categorized into six types, namely, light, fair, medium, olive, brown, and black colors [1]. The information of skin such as color and texture always used for clue for some application such as face detection [2-5], pornographic filtering [6-9], surveillance [4], image content filtering and content aware video compression [6-12], Biometric characteristic [1], etc. Skin color classification is often used as pre-processing in aforementioned applications. Normally, no query skin image is involved to detect skin, but the information of skin color has been taken beforehand. This information may derive from the training phase and stored in the human skin detection system. The main challenge of skin color detection is to develop a skin color classifier that is robust to the large variations in color appearance. Some color appearance variation such as skin appearance changes in color, intensity, and location of light sources, and other objects within the scene may cast shadows or reflect additional light. There are also many objects, which are easily confused with skin color. This is because skin-like materials are those that appear skin-colored under a certain illumination. There are many methods have been proposed in literature. Some of methods are based on linear separator, and others based on non-linear separator to discriminate between skin and non-skin groups.

The objective of this paper is to study the performance of skin color classifiers between linear and non-linear skin color classifiers with eight color models. The rest of the paper is organized as follows: Next section describes the background of skin color detection methods; Section (III) describes a methodology used in this paper; Section (IV) focus on Result and discussion. Finally, main conclusions are outlined in Section (V).

II. BACKGROUND

Skin color detection is a process to determine whether a desired pixel or a group of pixels belongs to skin or non-skin color. The presence of skin and non-skin can be determined by manipulating pixel color. There are two classification techniques can be used to classify skin and non-skin pixels; pixel-based and region-based classification techniques. The pixel-based classification is carried out at a pixel level where each pixel is classified separately based on its color properties. On the other hand, region-based classification is carried out based on group of pixels where spatial arrangements of a group of pixel properties are taken into consideration. Pixel-based technique is invariant in terms of size and orientation [2] and it can be considered fast in processing [3] while region-based technique need additional computer time to compute additional information such as texture information.

The goal of skin color detection is to build a decision rule that will discriminate between skin and non-skin pixels. Kakumanu et al. [4] summarized a large collection of research works on skin detection investigation in their survey paper. Many different modelling for discriminating between skin and non-skin regions are available in literature which can be grouped into four; explicitly defined skin region, parametric, non-parametric and dynamic skin distribution modelling techniques [3]. A simple technique for skin detection modelling is to implement one or several threshold to decide whether a pixel is skin or non-skin color while more advance modelling technique employed statistical approached. A technique that implement threshold is categorized into explicitly defined skin region while a technique that employed statistical approach can be categorized either into parametric or non-parametric. The dynamic skin distribution modelling technique was further subdivided by Martinkauppi [5] into parametric and non-parametric techniques. The parametric technique is used parameters such as mean and covariance to model skin color distributions. The examples of parametric technique such as single Gaussian model [3], Gaussian mixture model [6], maximum entropy model [7], elliptical boundary model [8] and linear discriminant analysis model [9]. Meanwhile, non-parametric is distribution free method, which does not rely on assumption that the data are drawn from a given probability distribution. The examples of non-parametric technique such as Histogram model [10], Bayes model [11], Look-up table model [12] and neural network model [13].

III. METHOD

A. Skin Images Datasets

There are few skin data images available for public access such as Compaq dataset [14] , Sigal dataset [15], TDSD dataset [16], and db-skin dataset [17]. The researchers in [14], [18], [19], [7], and [8] used the Compaq dataset in their experiment. This dataset consists of 6,818 annotated images. However, at this time of writing, the Compaq dataset is no longer available for public use [17]. Thus, most of researchers [17, 20-23] are used their own dataset.

In this paper, a new skin color image database was developed called SIdb (Skin images database) [9]consists of 357 skin color images which is collected from Corbis website [24] at the royalty free image section. The Corbis website provides a rich resource of skin and non-skin images suitable for content-based information retrieval. These skin images were divided into two parts, namely a training dataset, which is consists of 250 skin images and a testing dataset, which is consists of 107 skin images. In other words, the ratio between the training set image and test set image is 70:30. Besides that, the TDSD dataset that consists of 100 very good annotated skin images [16, 17] and the UChile [17] have been used as benchmark datasets.

B. Color Models

Color model is a method by which color can be specified, created, and visualized. A human defined a color by its attributes of brightness, hue, and colorfulness. A computer described a color using amounts of red, green, and blue phosphor emission required to match a color. A color is usually specified using three co-ordinates or parameters. These parameters describe the position of the color within the color model is being used.

The choice of color model can be considered as the primary step in skin color detection modelling. Several color models have been proposed in the literature for skin color detection methods. Different researchers have used varying color models and methods. Each of them has their own reason in choosing the color model in their research. However, it is still not clear which are the best color model to be used for skin detection using linear and non-linear skin color classifiers. According to Gomez and Morales [25], the transformation of color model from RGB to other color model will reduce the overlap between skin and non-skin pixels and also could be reduced problem caused varying illumination conditions. Some literatures confirmed that the use of a specific color model can improve performance of the skin color classifier [26, 27]. However, according to Albiol et al. [28] this is not exactly true because some skin color distribution models have been show suitable for specific color model.

Many researchers do not provide strict justification of their color model choice because of possibility to obtain acceptable skin detection results on limited dataset with almost any color model. Some researchers [6, 29-31] have been provided justification for optimality of their choice for the skin model they employed. Some researchers [25, 32-35] have been devoted to comparative analysis of difference color models used for skin color detection. For many color model limitations, many researchers have chosen most suitable color model for their skin color detection method. Therefore, different color models have been employed for different skin color distribution models such as RGB [11, 14, 22, 36, 37], RGB normalized [25], CIE-XYZ [8], HSV [38, 39], YCbCr [40], YIQ [18], YES [41], YUV [42], CIE-XYZ [13, 19, 43], and CIE-LUV [6].

RGB Color Model: The RGB color model is specified in terms of the three primary colors: red (*R*), green (*G*), and blue (*B*). It is originated from Cathode Ray Tube (CRT) display application when it is convenient to describe color as a combination of three colored rays (red, green, and blue).

The RGB color model is one of the most widely used color model for processing and storing of digital image data. It also used for internet images. There are high correlation between channels, significant perceptual non-uniformity mixing of chrominance and luminance data make RGB not a very favorable choice for color analysis and color based recognition algorithms [3].

One main advantage of the RGB color model is its simplicity and speed dealing with web images and in many cases skin color detection can be done directly on pixel value without color model conversion [44]. The luminance of a given RGB pixel is a linear combination of the *R*, *G*, and *B* values. Therefore, changing the luminance of a given skin patch affects all R, G, and B components [45]. In other words, the value of the RGB will differ based on the intensity of the illumination.

Despite the fundamental limitations aforementioned above, RGB color model extensively used in skin color detection literature [1, 7, 11, 18, 21, 22, 46-49]. Among the main reasons is its simplicity and yield quite satisfying performance. It has been also used extensively in the detection of pornographic image [50-52].

RGB Normalized Color Model: To reduce the dependence on lighting, RGB color component are normalized [4] to remove intensity information. Two components of RGB normalized color model have been proposed to minimize luminance dependencies [27]. RGB normalized is invariant to changes of surface orientation relative to the light source [53]. This, together with the transformation simplicity helped this color model to gain popularity among the researchers [19, 32, 54]. The RGB normalized color model can be computed as follows:

$$r = \frac{R}{(R+G+B)}) \tag{1}$$

$$g = \frac{G}{(R+G+B)} \tag{2}$$

$$b = 1 - r - g \tag{3}$$

where *R*, *G*, and *B* are the value of red, green, and blue, respectively.

Yang and Lu [29] and Yang and Ahuja [6] have concluded that the difference in skin color pixels due to lighting conditions and ethnicity can be greatly reduced by using RGB normalized color model. In addition, the skin color cluster in RGB normalized color model have relatively lower variance than the corresponding clusters in RGB color model and hence have shown to be a good method for skin color modelling and detection [6, 54, 55].

HSV Color Model: The HSV color model defines color as Hue (*H*), Saturation (*S*), and Value (*V*). The Hue is defined the dominant color such as red, green, purple, and yellow. This property is varies from red to green. Saturation (*S*) is defined the colorfulness of an area in proportion to its brightness. This property is varies from red to pink. When Saturation is set to 0, Hue is undefined. HSV color model has been used because is more related to human color perception [56]. The intuitiveness of the color model component and explicit discriminate between luminance and chrominance properties made this color model popular in the works on skin color detection [15, 32, 57]. It can form a very good choice for skin color distribution modelling [4].

The transformation of RGB to HSV is invariant to high intensity at white light, ambient light, and surface orientation relative to the light source [53]. The RGB values can be transformed to HSV color model by following equations:

$$H_1 = arccos\left(\frac{\frac{1}{2}((R-G)+(R-B)}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right)$$

$$H = \begin{cases} H_1, & if\ B \leq G \\ 360^0 - H_1, & if\ B > G \end{cases}$$

$$S = \frac{max(R,G,B) - min\ (R,G,B)}{max\ (R,G,B)}$$

$$V = \frac{max\ (R,G,B)}{255}$$

where *R*, *G*, and *B* are the value of red, green, and blue, respectively.

Orthogonal Color Models: The YCbCr and YIQ are orthogonal color models. The YCbCr is a digital color system, while YIQ are analogue space for the NTSC (National Television System Committee) systems. The YCbCr color model is sometimes referred to as the CCIR 601. These device-dependent color models are belong to the family of television transmission color model. This color model was defined in response to increasing demands for digital approaches in handling video information and has been used widely in digital video.

These color models separate RGB into luminance and chrominance. RGB values can be transformed to YCbCr and YIQ color model by the Equation (8) and Equation (9), respectively.

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 1 & 0.956 & 0.621 \\ 1 & -0.272 & -0.647 \\ 1 & -1.106 & 1.703 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

where *R*, *G*, and *B* are the value of red, green, and blue, respectively.

CIE-Lab Color Models: The first color model developed by the Commission Internationale de 1'Echairage (CIE) is the CIE-XYZ color model. The CIE-XYZ color model is a device-independent color model, but is perceptually not uniform. The Y component is the luminance component while Z and X are the chromatic components. A CIE-Lab color model is a color-opponent space with dimension L for lightness and *a* and *b* for the color model coordinates.

The *L* component always positive and represents brightness, $a > 0$ represents red component, $a < 0$ represent green component, $b > 0$ represents yellow component, and $b < 0$ represent blue component. This color model is derived from the CIE-XYZ color model is given by following equations:

$$L = 116f\left(\frac{Y}{Y_n}\right) - 16$$

$$a = 500\left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right)$$

$$b = 200(f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right))$$

where $f(t) = \begin{cases} t^{\frac{1}{3}}, & t < (\frac{6}{29})^3 \\ \frac{1}{3}(\frac{29}{6})^2 t + \frac{4}{29}, & otherwise \end{cases}$.

Here X_n, Y_n and Z_n are the CIE XYZ tristimulus values of the reference white point (the subscript *n* suggests normalized). The division of the *f(t)* function into two domain was done to prevent an infinite slope at $t=0$. *f(t)* was assumed to be linear below some $t=t_0$, and was assumed to match the $t^{1/3}$ part of the function at t_0 in both value and slope.

The CIE-XYZ can be achieved through a linear coordinate transformation of the RGB color model. The *Y* component corresponds to the brightness of the color (luminance). The chromaticity value (x, y) can be achieved by central projection into plane $X + Y + Z = 1$ and then projecting into the *XY* plane [58].

Despite the many advantages of CIE-Lab color model, they are rarely used in skin detection. This is mainly because the transformation from RGB color model is more computationally expensive as compared to transforming to other color model. The CIE-Lab color model has been used by Schumeyer and Barners [31], Cai and Goshtasby [59], Zarit et al. [32], Kawato and Ohya [60], and Ravichandran and Ananthi [23] in skin color detection.

LUX Color Models: The LUX color model is a nonlinear color model. This color model was used for skin detection because it provides more contrast between skin, lips, and other materials compared to YCbCr color model [61].

The Logarithmic Hue Extension (LUX) is a nonlinear color model introduced by Lievin and Luthon [61] for skin color detection. This color model is derived from a color difference coding space and can be expressed as follows:

$$L = (R+1)^{0.3}(G+1)^{0.6}(B+1)^{0.1} - 1)$$

$$U = \begin{cases} \frac{M}{2}\left(\frac{R+1}{L+1}\right), & if\ R < L \\ M - \frac{M}{2}\left(\frac{L+1}{R+1}\right), & otherwise \end{cases}$$

$$X = \begin{cases} \frac{M}{2}\left(\frac{B+1}{L+1}\right), & if\ B < L \\ M - \frac{M}{2}\left(\frac{L+1}{R+1}\right), & otherwise \end{cases}$$

where *R*, *G*, and *B* are the value of red, green, and blue, *M* is the dynamic range between 0 to 255. For example, the 8 bit data the value of *M* is 255. The *U* and *X* are the Chroma components. This color model provides more contrast between skin, lips, and other material than *CbCr* [61].

(10)

Opponent Color Models: The opponent color model is inspired by the human visual system that (11) can be expressed in terms of the two opponent hues, yellow-blue, and green-red which cancelled each other when (12) superimposed [62]. A log-opponent color model for skin color detection was suggested by Fleck et al. [63]. This color model can be derived from RGB color model using the following equations:

$$L(x) = 105log_{10}(x + 1 + n) \tag{16}$$

$$I = L(G))$$

$$R_g = L(R) - L(G))$$

$$B_y = L(B) - \frac{L(B)+L(R)}{2})$$

where *x* represents a value of either *R*, *G*, or *B*, *n* is a random noise value generated from a uniform distribution over the range [0, 1) and the constant 105 is used to scale the range to interval [-255 255]. This color model compresses the lower saturated achromatic color, e.g., skin color and stretches the more saturated colors which might result in an inferior separability of colors that are close to a chromatic [64].

C. Linear Discriminant Analysis

Discriminant analysis is a parametric technique to classify objects into mutually exclusive and exhaustive groups based on a set of measurable object's features. It is also often referred to as pattern recognition, supervised learning, or supervised classification. Conventionally, discriminant analysis is divided into two; linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). LDA occurred when population covariance matrices are equal; otherwise, it called QDA. These discriminant analysis are based on assumption that each group follows multivariate normal (Gaussian) distribution. Discriminant analysis is similar to regression analysis except that the dependent variable is categorical rather than continuous. In general discriminant analysis is a very useful tool for detecting the variables that allow to discriminate between different groups and for classifying cases into different groups with a better than chance accuracy. It has been widely used in many pattern recognition applications such as face, speech, fingerprint recognition, disease diagnosis and business decision-making [65].

D. *Neural Network*

Since linear LDA is designed to analyze datasets, which can be separated along an axis. It may give unacceptable results when used for datasets with even slightly overlapping classes. This due to the difficulty to select features those significantly able to classify between two classes clearly and thoroughly. In such case, Chen et al. [66] suggested that the non-LDA methods such as artificial neural network could be useful. A neural network (NN) is an information processing paradigm that is inspired by the way biological nervous systems such as the brain. It is composed of a large number of highly interconnected processing neurons working in unison to solve specific problems.

The NN is a non-parametric method which has been proven as powerful tools to solve problems in signal processing and pattern recognition fields. The most critical advantage of using a NN is their adaptive learning capability, which enables NN to be taught to interpret possible variations of target objects. NN has the ability to learn complex data structure from a set of example patterns [67]. It has the advantages of working fast after the training phase even with large amount of data.

Figure 1 illustrates the NN architecture used for skin detection in this paper. The value of input (x_i) id represented for value of each color component and the output value (y_k) is value range between zero (non-skin) and one (skin).

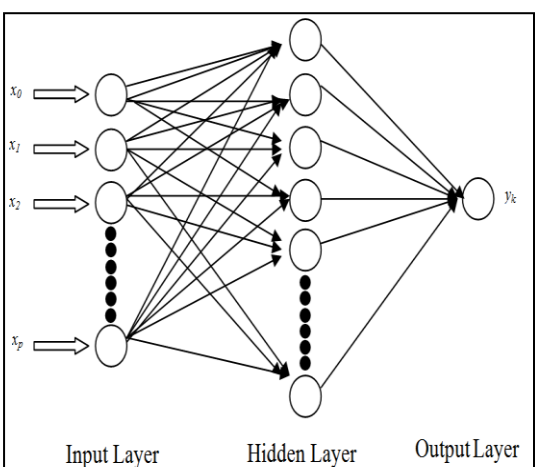

Figure 1. Neural network architecture for skin detection

IV. RESULT AND DISCUSSION

A. *Linear Discriminant Analysis*

The linear discriminant analysis (LDA) method has been carried out for pixel-based skin color detection. The LDA carried out to formulate a linear discriminant function and skin and non-skin group centroids. For the two group's classification, the LDA will produces one linear discriminant function. This function which called skin color classifier have been used to classify pixels into skin and non-skin groups. The performance of classifiers were measured based on true positive (TP) and false positive (FP) indicator. The performances of skin color classifiers formulated from training were tested to the testing dataset, SIdb and also to the benchmark datasets; UChile and TDSD datasets.

Table 1 shows the performance of skin color classifier formulated for each color model. The performance of classifiers are rank based on lowest FP with high TP [3]. In other words, the lowest FP with high TP is considered the better skin color detection rate.

Regardless of the choice of the color model and the classification method used, most published research [3, 4, 28, 32, 33, 64] on skin color detection reports about 5% to 30% of FP, and 80% to 95% of TP. Some researchers [68, 69] have been reported that skin color classifier performance based on TP only. Thus, this paper, the performance of skin color classifiers based on FP value was grouped into three, namely; good, moderate, and poor as follows:

i. Good: FP is equal and less than 15%.
ii. Moderate: FP is greater than 15% to 30%.
iii. Poor: FP is greater than 30%.

This grouping is used to classify the performance of classifier clearly and as a guidance to categorize the skin color detection performance. Based on the grouping above, the performance of skin color classifier for each color model using LDA can be grouped as shown in Table 2.

Table 1: Linear discriminant analysis result

Color model	SIdb		UChile		TDSD		AVERAGE	
	TP	FP	TP	FP	TP	FP	TP	FP
RGB	82.72	15.47	78.57	20.16	97.05	36.11	86.11	23.91
HSV	87.38	21.73	83.61	25.06	98.29	45.60	89.76	30.80
YIQ	82.56	15.41	78.34	20.05	96.98	36.02	85.96	23.83
YCbCr	79.16	13.77	75.45	16.24	96.41	30.65	83.67	20.22
LUX	87.20	32.48	88.74	31.78	98.37	54.67	91.44	39.64
rgb	83.85	27.71	90.15	32.35	90.33	37.31	88.11	32.46
IRgBy	91.90	44.47	86.98	40.75	98.61	59.50	92.50	48.24
Lab	77.43	12.39	92.29	0.40	95.67	27.38	88.46	13.39

Table 2: Performance of skin color classifier for each color model using LDA

Performance	Color model
Good	CIE-Lab
Moderate	RGB, YIQ, YCbCr
Poor	HSV, LUX, rgb, Opponent

The CIE-Lab color model shows most superior as compared to other color models and fall in the first group. This is because CIE-Lab color model result shows lowest average of FP. This means, the CIE-Lab color model is more suitable color model to use for developing skin color distribution model using LDA.

The RGB, YIQ, and YCbCr color models are fallen in moderate group. Meanwhile HSV, LUX, RGB normalized, and opponent color models are grouped in poor group. This means, these color models are not suitable to use with LDA method to model skin color distribution.

B. Neural Network

The NN has been carried out for each color model as used in LDA experiment. The output of NN is a non-linear skin classifier. The performance of classifier were measured based on TP and FP indicator which showed in Table 3.

The performances of skin color classifiers formulated from training were tested to the testing dataset, SIdb and also to the benchmark datasets; UChile and TDSD datasets.

The performance of skin color classifier using NN can be grouped as shown in Table 4.

Table 4: Performance of skin color detection for each color model using NN method

Performance	Color model
Good	CIE-Lab, RGB, HSV, YIQ, YCbCr
Moderate	rgb, Opponent
Poor	LUX

Table 4 shows that there are more color models that were grouped into first group. This means, more color models are suitable to be used with NN method to model skin color distribution. Furthermore, the separation between skin and non-skin pixels most like to non-linear technique. Table 4 also shows that the CIE-Lab, RGB, HSV, YIQ, and YCbCr color models are grouped in Good category and RGB Normalized and Opponent color models are grouped in Moderate, while LUX color model is not suitable to model skin color distribution using NN, which it fall into poor group.

Table 3: Performance of skin color detection using NN method

Color model	SIdb		UChile		TDSD		AVERAGE	
	TP	FP	TP	FP	TP	FP	TP	FP
RGB	97.67	6.72	81.04	11.99	93.48	23.97	90.73	14.23
HSV	82.93	7.99	78.97	11.80	94.79	23.87	85.56	14.55
YIQ	82.32	7.50	77.08	11.64	93.16	23.13	84.19	14.09
YCbCr	82.38	7.83	83.34	12.85	95.17	23.65	86.96	14.78
LUX	98.27	53.62	97.17	53.07	96.97	71.68	97.47	59.46

rgb	87.86	17.29	80.34	20.03	88.33	29.23	85.51	22.18
Opponent	61.75	13.70	78.73	12.39	94.98	25.97	78.49	17.35
CIE-Lab	81.88	7.59	81.22	10.11	94.32	20.18	85.81	12.63

V. CONCLUSION

This paper presented an experiment to develop skin color classifier using linear and non-linear method. LDA is represented a linear method while NN is represented a non-linear method. Most color models showed high performance in terms of FP when using NN compared to LDA method to develop skin color classifier except for LUX color model.

The performances of skin color classifiers have been grouped into three; Good, Moderate, and Poor based on FP value. The results from statistical methods; LDA and NN show that the CIE-Lab color model is the best color model used to formulate skin color classifier as compared to other color models. The other color models such as RGB, HSV, YIQ, YCbCr also promising a good result can be used in developing skin color distribution model based on statistical method. Meanwhile, the LUX, RGB normalized, and Opponent color models are not performed well when using statistical method to develop skin color distribution model. Thus, these color models are not recommended for developing skin color distribution model using linear or non-linear based methods.

Table 5 shows comparison between classifiers formulated using LDA and NN.

Table 5.8: Comparison between LDA and NN method

Color model	LDA		NN		Improvement	
	TP	FP	TP	FP	ΔTP	ΔFP
RGB	86.11	23.91	90.73	14.23	4.62	-9.68
HSV	89.76	30.80	85.56	14.55	-4.20	-16.25
YIQ	85.96	23.83	84.19	14.09	-1.77	-9.74
YCbCr	83.67	20.22	86.96	14.78	3.29	-5.44
LUX	91.44	39.64	97.47	59.46	6.03	19.82
rgb	88.11	32.46	85.51	22.18	-2.60	-10.28
Opponent	92.50	48.24	78.49	17.35	-14.01	-30.89
CIE-Lab	88.46	13.39	85.81	12.63	-2.65	-0.76

The negative sign for TP at improvement column indicates that the performance of the method is decreased, meanwhile negative sign for FP at improvement column indicates that the performance of the method is increased.

In general, the value of TP is trade-off with FP, meaning that, when TP increased, FP will decrease except in case of RGB and YCbCr color models, which are shown better performance.

The classifier formulated using CIE-Lab color model shows very little improvement as compared between LDA and NN. It can be concluded that using the CIE-Lab color model produced consistent performance whether using parametric or non-parametric based methods to model skin color distribution. This means, transformation from RGB color model to CIE-Lab significantly contribute to separate between skin and non-skin color.

When skin color detection is used for pre-processing to the further process such hang tracking, face detection, people detection, pornographic filtering, etc. The RGB color model is the most suitable color model to be used because of high TP rate with little big compromised FP rate. This is also because transformation from RGB color model to other color model will cost extra computer time or processing, especially for transformation from RGB to CIE-Lab color model. The transformation of RGB color model to CIE-Lab will take two steps, the RGB color model have to transform to XYZ color model before transform to CIE-Lab color model. It will affect to online processing in skin color detection application. However, if processing time is not a major factor and when skin color detection is solely used for some application, the CIE-Lab color model is the most suitable color model for skin color detection.

ACKNOWLEDGEMENTS

This research is funded by Universiti Teknologi MARA. We wish to express my sincere appreciation to Professor Javier, Ruiz-del-Solar [17] from Universidad de Chile and Professor Hsu, Rein-Lien [46] from Michigan State University for their skin images database.

REFERENCES

[1] R. D. Kalambe, R. Pandit, and S. Patel, "Survey paper of encrypted data hiding using skin tone detection," *International Journal of Computer Applications*, vol. 79, 2013.

ISSN:2319-7900

[2] F. Boissaid, A. Bouzerdoum, and D. Chai, "VLSI Implementation of a Skin Detector Based on a Neural Network," *IEEE,* vol. 5, pp. 1561-1564, 2005.

[3] V. Vezhnevets, V. Sazonov, and A. Andreeva, "A Survey on Pixel-Based Skin Color Detection Techniques," *Graphicon,* pp. 85-92, 2003.

[4] P. Kakumanu, S. Makrogiannis, and N. Bourbakis, "A survey of skin-color modeling and detection methods," *Pattern Recognition,* vol. 40, pp. 1106-1122, 2007.

[5] B. Martinkauppi, "Face colour under varying illumination - Analysis and applications," Department of Electrical and Information Engineering, University of Oulu, Finland, 2002.

[6] M. H. Yang and N. Ahuja, "Gaussian mixture model for human skin color and its applcation in image and video databases," in *Conference on Storage and retrieval for Image and Video Databases*, 1999, pp. 458-466.

[7] B. Jedynak, H. Zheng, M. Daoudi, and D. Barret, "Maximum entropy models for skin detection," Universite des Science et Technology de Lille, France, Technical report, 2002.

[8] J. Y. Lee and S. I. Yoo, "An Elliptical boundary model for skin detection," *Proceeding of International conference on imaging science, system, and technology,* 2002.

[9] G. Osman and M. S. Hitam, "Skin colour calssification using linear discriminant analysis and colour mapping co-occurrence matrix," in *International Conference on Computer Application Technology*, Tunisia, 2013, pp. 1-5.

[10] V. Vezhnevets and A. Andreeva, "A comparative assessment of pixel-based skin detection methods," Moscow State University, Graphics and Media Lab, Technical Report, 2005.

[11] M. J. Jones and J. M. Rehg, "Statsitical color models with application to skin detection," *IEEE Conference on Computer Vision and Pattern Recognition 1999,* pp. 274-280, 1999.

[12] R. Kjeldsen and J. Kender, "Finding skin in color images," presented at the Proceedings of the 2nd International Conference on Automatic Face and Gesture Recognition (FG '96), 1996.

[13] C. Chen and S. P. Chiang, "Detection of human faces in colour images," *IEEE Proceedings Visual Image Signal Process,* vol. 144(6), pp. 384-388, 1997.

[14] M. J. Jones and J. M. Rehg, "Statistical color models with application to skin detection," Compaq Cambridge Research Lab, Technical Report, 1998.

[15] L. Sigal, S. Sclaroff, and V. Athitsons, "Skin color-based video segmentation under time-varying illumination," *IEEE Trans. on Pattern Analysis and Machine Intelligence,* vol. 26, pp. 862-877, July 2004.

[16] Q. Zhu, C.-T. Wu, K.-T. Cheng, and Y.-L. Wu, "An Adaptive Skin Model and Its Application to Objectionable Image Filtering," in *Proceedings of ACM Multimedia 2004*, New York, USA, 2004, pp. 56-63.

[17] J. Ruiz-del-Solar and R. Verschae, "SKINDIFF - Robust and fast skin segmentation," Department of Electrical Engineering, Universidad de Chile. 2006.

[18] J. Brand and J. Mason, "A comparative assessment of three approaches to pixel level human skin-detection," *International conference on pattern recognition,* vol. 1, 2000.

[19] D. Brown, I. Craw, and J. Lewthwaite, "A SOM based approach to skin detection with application in real time system," *Proceeding of British machine vision conference,* 2001.

[20] T. S. Caetano, S. D. Olabarriaga, and D. A. C. Barone, "Performance evaluation of single and multiple-gaussian models for skin color modeling," in *Brazilian Symposium on Computer Graphics and Image Processing.* 2002.

[21] J. Kovac, P. Peer, and F. Solina, "Human skin colour clustering for face detection," in *Proceeding of EUROCON 2003. Computer as a Tool. The IEEE Region 8*, 2003, pp. 144-148.

[22] A. A.-S. Saleh, "A simple and novel method for skin detection and face locating and tracking," in *APCHI 2004, LNCS 3101*, 2004, pp. 1-8.

[23] K. S. Ravichandran and B. Ananthi, "Color skin segmentation using k-means cluster," *International Journal of Computational and Applied Mathematics,* vol. 4, pp. 153–157, 2009.

[24] Corbis. Corbis. Internet photo store [Online]. Available: http://www.corbis.com

[25] G. Gomez and E. Morales, "Automatic feature construction and a simple rule induction algorithm for skin detection," in *Proceeding of ICML Workshop on Machine learnong in computer vision*, 2002.

[26] C. H. Lee, J. S. Kim, and K. H. Park, "Automatic human face location in a complex background using motion and colour information," *Pattern Recognition,* vol. 29, pp. 1877-1889, 1996.

[27] J. G. Wang and E. Sung, "Frontal-view face detection and facial feature extracting using colour and morphological operators," *Pattern recognition,* vol. 20, pp. 1053-1068, October 1999.

[28] A. Albiol, L. Torres, and E. J. Delp, "Optimum colour spaces for skin detection," in *International Conference on Image Processing*, Thessaloniki, Greece, 2001, pp. 122-124.

[29] J. Yang, W. Lu, and A. Waibel, "Skin-color modeling and adaptation," presented at the ACCCV 1998.

[30] M. Storring, H. J. Anderson, and E. Granum, "Skin colour detection under changing lighting condition," in *7th Symposium on Intelligent Robotics Systems*, 1999, pp. 187-195.

[31] R. Schumeyer and K. Barner, "A color-based classifier for region identification in video," in *Visual Communications and Image Processing*, SPIE, 1998, pp. 189-200.

[32] B. D. Zarit, B. J. Super, and F. K. H. Quek, "Comparison of five color models in skin pixel classification," in *Proceeding of ICCV'99 Int'l Workshop on recognition, analysis and tracking of faces and gestures in Real-time system*, 1999, pp. 58-63.

[33] J. C. Terrillon, M. N. Shirazi, H. Fukamachi, and S. Akamatsu, "Comparative performance of different skin chrominance models and chrominance spaces for the automatic detection of human faces in color images," *Proceedings of the International Conference on Face and Gesture Recognition,* pp. 54-61, 2000.

[34] G. Gomez, "On selecting colour component for skin detection," in *ICPR 2000*, 2000, pp. 961-964.

[35] H. Stern and B. Efros, "Adaptive color space switching for face tracking in multi-colored lighting environments," in *International conference on automatic face and gesture recognition*, 2002.

[36] M. J. Jones and J. M. Rehg, "Skin colour modelling and detection," hp-labs, Cambridge Research Laboratory. 2002.

[37] J. Kovac, P. Peer, and F. Solina, "2D versus 3D colour space face detection," vol. 2, pp. 449-454, 2003.

[38] C. Garcia and G. Tziritas, "Face detection using quantized skin colour regions merging and wavelet packet analysis," *IEEE Trans. on Multimedia*, vol. 1, pp. 264-277, 1999.

[39] S. Tsekeridou and I. Pitas, "Facial feature extraction in frontal views using biometric analogies," in *11st European Signal Proceeding Conference*, 1998, pp. 315-318.

[40] D. Chai and K. N. Ngan, "Face segmentation using skin-color map in videophone application," *IEEE Trans. on Circuits and System for Video Technology*, vol. 9, pp. 551-564, 1999.

[41] E. Saber and A. M. Tekalp, "Front-view face detection and facial feature extraction using color, shape and symmetry based cost functions," *Pattern Recognition Lett.*, vol. 17, 1998.

[42] F. Marques and V. Vilaplana, "A mophological approach for segmentation and tracking of human race," in *ICPR 2000*.

[43] H. Wu, Q. Chen, and M. Yachida, "Face detection from volor images using a fuzzy pattern matching method," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 21, pp. 557-563, 1999.

[44] M. J. Jones and J. M. Rehg, "Statistical color models with application to skin detection," *International Journal of Computer Vision*, vol. 46, pp. 81-96, 2002.

[45] A. Elgammal, C. Muang, and D. Hu, "Skin detection," *Encyclopedia of Biometrics*, 2009.

[46] T. Hsu, M. Abdel-Mottaleb, and A. Jain, "Face Detection in Colour Images," *IEEE Trans*, vol. 5, 2002.

[47] S. L. Phung, A. Bouzerdoum, and D. Chai, "Skin segmentation using color pixel classification: Analysis and comparison," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, pp. 148-154, 2005.

[48] G. Osman, M. S. Hitam, and M. N. Ismail, "Enhanced skin colour classifuer using RGB ratio model," *International Journal on Soft Computing*, vol. 3, pp. 1-14, 2012.

[49] G. Osman and M. S. Hitam, "Skin color classification using color mapping co-occurrence matrix," *Journal of Information Organization*, vol. 1, pp. 12-22, 2013.

[50] W. Kelly, A. Donnellan, and D. Molloy, "Screening for objectionable images: A review of skin detection technique," in *Int. Machine Vision and Image Processing*, 2008, pp. 151-158.

[51] J. Ruiz-del-Solar, V. Castaneda, R. Verschae, R. Baeza-Yates, and F. Ortiz, "Characterizing objectionable image content (Pornography and nude images) of specific Web segments: Chile as a case study," in *3rd Latin American Web Congress*, 2005.

[52] H. Zheng, M. Daoudi, and B. Jedynak, "Blocking adult images based on statistical skin detection," *Electronic Letters on Computer Vision and Image Analysis*, vol. 4, pp. 1-14, 2004.

[53] W. Skarbek and A. Koschan, "Colour image segmentation - a survey," Technical University of Berlin, Berlin. 1994.

[54] M.-H. Yang and N. Ahuja, "Detecting human faces in color images," in *International Conference on Automatic Face & Gesture Recognition*, 1998, pp. 127-130.

[55] M. H. Yang, D. Kriegman, and N. Ahuja, "Detecting faces in images: A survey.," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24(1), pp. 34-58, Jan 2002.

[56] K. Sobottka and I. Pitass, "Face localization and facial feature extractin based on shape and color information," *IEEE Int. Conf. on Image Processing*, vol. III, pp. 483-486, 1996.

[57] L. Jordao, M. Perrone, J. Costeira, and J. I. Santos-Victor, "Active face and feature tracking," in *Proceeding of 10th International conference on image analysis and processing*, 1999.

[58] K. N. Poyton, *A Technical Introduction to Digital Video*: John Wiley & Sons, 1996.

[59] J. Cai and A. Goshtasby, "Detecting human faces in color images," *Image Vision Computation*, vol. 18, pp. 63-75, 1999.

[60] S. Kawato and J. Ohya, "Automatic skin-color distribution extraction for face detection and tracking," in *5th International Conference on Signal Processing*, 2000, pp. 1415-1418.

[61] M. Lievin and F. Luthon, "Nonlinear color space and apatiotempral MRF for hierarchical segmentation of face feature in video," *IEEE Trans. on Image Processing*, vol. 13, pp. 63-71, Jan. 2004.

[62] K. N. Plataniotis and A. N. Venetsanoupoulos, *Color image processing and application*. Berlin, Germany: Springer, 2000.

[63] M. M. Fleck, D. A. Forsyth, and C. Bregler, "Finding naked people," presented at the 4th European Conf. on Computer Vision, Cambridge, UK, 1996.

[64] M. Storring, "Computer Vision and Human Skin Colour," Ph.D. Ph.D. Dissertation Computer Vision & Media Technology Laboratory. Aalborg University, Denmark, 2004.

[65] C. Been-Chian, L. Jung Yi, and H. Tzung-Pei, "Learning discriminant functions with fuzzy attributes for classification using genetic programming," *Expert System with Application*, vol. 23, pp. 31-37, 2002.

[66] Z.-P. Chen, J.-H. Jiang, Y. Li, Y.-Z. Liang, and R.-Q. Yu, "Fuzzy linear discriminant analysis for chemical data sets," *Chemometrics and Intelligent Laboratory Systems*, vol. 45, pp. 295–302, 1999.

[67] J. Zurada, *Introduction to artificial neural systems*: PWS Publishing Co., 1992.

[68] C. Anagnostopoulos, I. Anagnostopoulos, D. Vergados, I. Papaleonidopoulos, E. Kayafas, V. Loumos, *et al.*, "A probabilistic neural network for face detection on segmented skin areas based on fuzzy rules," 2002, pp. 493-497.

[69] S. Jayaram, S. Schmugge, and L. V. T. Min C. Shin, "Effect of colorspace transformation, the illuminance component, and color modeling on skin detection," in *Conference on Computer Vision and Pattern Recognition (CVPR'04)*, Washington DC, 2004, pp. 813-818.