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Survey on Skin Tone Detection using Color Spaces

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ABSTRACT
Skin is arguably the most widely used primitive in human image processing research and computer vision with application ranging from face detection and person tracking to pornography filtering. It has proven to be useful and robust cue for detecting human parts in images since (i) it is invariant to orientation and size (ii) it gives extra dimension compared to gray scale methods and (iii) it is fast to process. The main problems with the robustness of skin color detection are however depends on illumination condition, it varies between individuals, many everyday life objects are skin color like and skin color is not unique. Environments comprehensive survey in this topic is missing. The work presented in this paper is a survey of the most frequently used methods and techniques and their numerical evaluation results.

General Terms
Image Processing, Face Detection.

Keywords
Color Space information, Color Transform, Image Segmentation, and Skin Detection.

1. INTRODUCTION
Human skin detection is most import in numerous applications such as facial analysis, gesture analysis, video surveillance, human machine interface, cyber crime prosecution, image content filter, content aware video compression, annotation, color balancing applications and image retrieval.

Skin detection means detecting image pixels and regions that contain skin tone color. Instead of using feature based face detection methods, using skin color for detection have gained strong popularity. Skin detection using color information can be seen from two points: one is a problem of 'color classification' and other is a problem of 'color image segmentation'.

In this paper, pixel based skin detection methods are discussed. In pixel based method, each pixel is classified as skin and non skin individually, independently from its neighbors. Color based methods fall on this category. In contrast, region based method is to take the spatial arrangement of skin pixels into account during the detection stage to enhance the methods performance. Additional knowledge such as texture etc is required. Region based methods are built on top of the pixel based ones. So this paper focuses on pixel based approaches only. It is a standard binary classification problem where the input is a color vector and the output will be a skin and non skin. Classification like this is commonly referred to as 'pallet reorganization'. So skin detection is a problem of pattern recognition. Three major approaches are used in pattern recognition such as statistical, neural and symbolical. Among various frameworks, statistical approach has been studied and most widely used in skin detection based on color information.

The rest of this paper is arranged as follows. Section 2 describes the different color spaces used for skin detection. Section 3 covers the existing skin color modeling methods. Comparison and discussion is given in section 4 and conclusion is drawn in section 5.

2. SKIN COLOR REPRESENTATION
In image processing and computer vision, color can be used as a powerful descriptor to identify objects (or) extract features. Yet, color remains challenging to describe. Several color representations have been proposed. Each has its own advantages and reasons for being used in practice. This section reviews the most widely used color spaces for skin detection and their properties.

2.1 Basic Color Spaces

2.1.1. RGB
RGB is the most commonly used color space to represent digital images, since most of the image display devices have some sort of RGB output. It is being used in every computer systems as well as videos, cameras etc [41]. Moreover RGB benefits from its simplicity and easiness of implementation. It is not a favorable choice for color analysis and color based reorganization system because of its high correlation between the channels, significant perceptual non uniformity, mixing of chrominance and luminance data.[2]. This color space was used in [12], and [13].

2.1.2. Normalized RGB
Normalized RGB is obtained by normalizing RGB value to their first normalization using the following equation.

$$r= R/R+G+B \text{ , } g=G/R+G+B, \ b=B/R+G+B. \quad (1)$$

It is actually to reduce the dependencies of RGB values on changing its illumination i.e. to separate luminance from chrominance. It is obvious that-(r+g+b=1) and by having any two components of r, g and b, third component can be obtained. Some authors [5] and [42] used r-g component as a sort of luminance. Separating luminance from chrominance is the desired goal for color space detection. On account of this advantages and simplicity in transformation, n-RGB gains popularity among researchers.

2.1.3: CIE XYZ

The CIE system describes color as a luminent component and two additional components X and Z. CIE-XYZ values were constructed from psychophysical experiments and correspond to the color matching characteristics of human visual system.

2.2 Perceptual Color Spaces (HIS,HVS,HSL,TSL)

2.2:1: HSV

HSV- Hue, Saturation and value was first introduced by Alay Ray Smith in 1978. V is the level of brightness. This color model is a simple and linear transformation from RGB. Hue defines the dominant color [such as red, purple and yellow] of an area. Saturation measures the colorfulness of the area in proportion of the brightness of the image. The conversion of RGB to HSV is given by the following equations. Note that there is no standard way to convert RGB to HSV.

$$H = \begin{Bmatrix} HiifB \leq C \\ 360 - HiifB > C \end{Bmatrix} \quad (2)$$

Where

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

$$S = \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)} \quad (3)$$

$$V = \frac{\max(R,G,B)}{255} \quad (4)$$

The separability of chrominance and luminance is achieved in this space. Some other important properties are invariant to highlight, surface orientation etc. These properties make this color space popular on their color segmentation [5].

Some undesirable features of this color space noted including hue discontinuities and the compilation of brightness were found which conflicts badly with the properties of color vision.

Qiong Liu et al [28] used HS color space for skin detection. Their algorithm detects faces with different sizes, rotations and expressions under different illumination conditions fast and accurately.

2.2.2: TSV and TSL

TSV and TSL-Tint, Saturation and value (Lightness) were used in skin detection [15]. These spaces are more complex alternative to HSV.

$$T = \begin{Bmatrix} \frac{\frac{1}{2\pi}\arctan r'}{g'} + \frac{3}{4} ifg' < 0 \\ 0 ifg' = 0 \\ \frac{\frac{1}{2\pi}\arctan r'}{g'} + \frac{1}{4} ifg' > 0 \end{Bmatrix} \quad (5)$$

Where r’=r-1/3,g’=g-1/3

$$S = \sqrt{\frac{9}{5}}\left(r'\uparrow 2 + g'\uparrow 2\right) \quad (6)$$

$$V = \frac{R+G+B}{3} \;\&\; L = 0.299R + 0.587G + 0.114B \quad (7)$$

TSL is really best choice of color space for ‘Gaussian Skin color Modeling’ [2].

2.3 Orthogonal Color Spaces (YC_bC_r,YIQ,YUV,YES)

This color space i.e. YC_bC_r is commonly used by European TV system. Luminance (Y) and chrominance (C_b and C_r) are used to represent this color space.

$$Y = 0.299R+0.587G+0.114B. \quad (8)$$

$$C_b = B-Y \quad (9)$$

$$C_r = R-Y. \quad (10)$$

In this color space, chrominance and luminance are explicitly separated. This property and its simplicity made this color space is one of the most popular color space used in skin detection [17], [9]. Other Orthogonal color spaces such as YC_gC_r was used in [10]. YUV in [44], YES in [45] and YIQ in [12].

2.4Perceptually Uniform Color Spaces

2.4.1: CIE-XYZ and CIE-xyY.

This representation is one of the first mathematically defined color spaces which is based on additive color models. Colors are described by three imaginary primitives X, Y and Z. Normalized values can be obtained by

$$x = \frac{X}{X+Y+Z}, y = \frac{Y}{X+Y+Z}, z = \frac{Z}{X+Y+Z} \quad (11)$$

In CIE-xyY , Y is also normalized from 0 to 100.

2.4.2: CIE CUV and CIE LAB

These are the non linear transformation of CIE Yxy. CIE CUV is offering a much better perceptual uniformity compared to its predecessors.

Both are device independent color spaces. Luminance and chrominance are very well separated. Finally both are reasonably perceptually uniform color system. These are not favorable in skin detection of its complexity and computational expensiveness.

These color spaces were used in [15] and [4].

2.4.3: Specific Color Space

It has been observed that skin contains a significant level of red. Hence, some researchers have used color ratios (e.g R/G) to detect skin. Gomez et al [11] selected color components for skin detection. He used attribute selection approach to select different complimentary color components from various color spaces. He considered that the hybrid 3D space : E-R/G-H and H-GY-Wr are reliable colors space for skin detection. Also the author argues that this new mixture space is not sensitive to noise from a wide range of unconstrained sources and illumination conditions. Brand and Mason [12] have evaluated the performance of color ratios with other algorithms on the Compaq data set. They concluded that the combinations of color ratios (R/G + R/B = G/B) provided better response than the individual ratios. Jouglas and Jacques [39] showed that adequately mixing color spaces can improve the detection of human skin, even if images are collected from many different sources. They concluded that the combinations of HSV-rgb-TSL have succeeded in segmenting a mixture of Asian, Caucasian and Black skins and excluding glass and hair.

Zhang and Shi [38] presented a detection based on uniting YC_bC_r color space with YC_gC_r color spaced. Their experimental result show that this method is simple and fast and also preserve skin color better than previous methods.

Recently Cheddad et al [35] developed a new segmentation method based on RGB color space. They argue that their method is insensitive with ethnicity and robust to illumination as well. They have also mentioned that their method is not intelligent enough to discriminate whether a scene contains a skin color or something that look like similar to this.

3. SKIN COLOR MODELING

The main goal of any skin detection system is to discriminate between skin and non-skin pixels. So skin detection is a two class problem. This section provides a brief description about most commonly used methods.

3.1 Explicitly Defined Skin Region

Human skin occupies a small region in color space [3]. Hence one of the easiest methods to build a skin classifier is to define explicitly the boundaries of skin cluster in some color spaces. Usually, single or multiple ranges of threshold values for each component of a color space are defined. For e.g. RGB is classified as skin if

$$R > 95 \;\&\; G > 40 \;\&\; B > 40 \text{ and}$$
$$(\max\{R,G,B\} - \min\{R,G,B\}) > 15 \text{ and}$$
$$|R-G| > 15 \;\&\; R > G \;\&\; R > B \quad (12)$$

This method is most obvious method because of its simplicity which has attracted by many researchers [43]. I component in YIQ space is also used for detecting skin pixels in which yellow people are present. The range of I component RI= [0, 50] [44]. HS space is used to detect skin. The range HS of RH=[0, 50] and RS=[0.23, 0.68] are defined as skin pixels. Wang & Yuan [45] have concluded in HSV space that an efficient combination is

$$H \in [0,50] \cup [340,360], S \in [0.2,1], V \in [0.35,1] \quad (13)$$

Sobottka I Pitas [44] have obtained good results by applying the following range

$$H \in [0,50], \quad S \in [0.23,0.68] \quad (14)$$

Garcia and Tziritas [46] have succeeded in skin segmentation by using

$$S \geq 10, V \geq 40V, S \leq 110 - H - 0.1V \text{ or } H \leq 750.4V \quad (15)$$

For TSL space the defined region is taken as

$$T \in (0.4,0.6), S \in (0.038) \quad (16)$$

Fixed range skin color map is also proposed for CbCr Plan. Cb= [77, 127] and Cr= [133, 173] are defined as skin pixels. Handaru Jati et al (2008) proposed the defined skin region as

$$100<Cb<150,\ 130<Cr<160 \;\&\; 0.01<H<1 \quad (17)$$

This span of parameter identified the majority of skin region but still detected animal skin in which the parameter value are similar to human skin.

3.2 Non Parametric Methods

The key idea of non parametric model is to estimate skin distribution from training data without deriving an explicit model for the skin color. The advantage of this method is that they are theoretically independent to the shape of this distribution.

3.2.1: Histogram model

In this method, color space is represented as 2D or 3D color histogram. Each color space is quantized into a no of bins where each bin stores the count associated with the occurrence of the bin color in the training data set. After training, histogram counts are normalized, converting histogram values to describe probability distribution which is given by

$$Pskin\ (c) = Count\ (c)/\ Norm. \quad (18)$$

Where Norm is Normalization coefficient which is the

sum of all histogram bin values. The color is then classified as skin if its likelihood value is greater than a predefined threshold. c is skin if Pskin (c) > threshold. Threshold value is determined from ROC. Several researchers used this method [24].

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3.2.2: Bayes classifier

Some researchers used conditional probability instead of Pskin (c) for smoother measure for skin detection, given the color c. This is more appropriate method because color c is the input of the classifier.

$$P\left(\frac{skin}{c}\right) = \frac{P\left(\frac{c}{skin}\right) \times P(skin)}{P\left(\frac{c}{skin}\right) \times P(skin) + P\left(\frac{c}{\sim skin}\right) \times P(\sim skin)} \quad (19)$$

P(c/skin) and P(c/~skin) are directly computed from skin and non skin histogram. The priors P(skin) and P(~ skin) can also be calculated from the overall no of skin and non skin in the training set. [13]

3.2.3: Self Organizing Map (SOM) classifier

SOM is one of the most popular types of unsupervised Artificial Neural Network (ANN). It serves as a clustering tool for both low and high dimensional data.

Brown et al trained two separate SOMs to learn skin and non skin distributions on a data set of over 500 images. SOM is also compared against Gaussian Mixture Model (GMM) and various color spaces (HS,XY,TS,rg) The SOM consistently performed better than GMMs in author's data set but in Compaq data set the SOM is superior to the RGB histograms in [13]. The author stress out that SOM method needs considerably less resource than histogram and mixture model and is efficiently implemented for run time applications by means of SOM hardware.

3.3 Parametric Methods

Many researchers have presented parametric methods that require less training data and more compact .Most popular methods are the single Gaussians model, mixture of Gaussians and Elliptical boundary model.

3.3.1: Single Gaussian Model

Some color distribution can be modeled by Gaussian probability density function, given by

$$P\left(\frac{c}{skin}\right) = \frac{1}{2\pi\sqrt{|\Sigma s|}} e^{-\frac{1}{2}(c-\mu s)T\Sigma s(c-\mu s)} \quad (20)$$

Where c is the color vector, μs is the mean vector and ∑s is the co- variance. The model parameters are estimated from the training data by

μs=

$$\frac{1}{n}\sum_{j=1}^{n} cj, \qquad \Sigma s = \frac{1}{n-1}\sum_{j=1}^{n}(cj-\mu s)(cj-s) \quad (21)$$

Where n is the total no. of skin color samples.
This method is employed by Hue et al [9] and Yang et al [4]

3.3.2: Mixture of Gaussians

It is the generalization of single Gaussions, the probability density function (pdf) is given by

$$P(c/skin) = \sum_{i=1}^{k} \pi i Pi\left(\frac{c}{skin}\right) \quad (22)$$

Where k is the no of mixture components and πi are the mixing parameters such that $\sum \pi i = 1$ the mixture model with Expection-Maxmization can also be found in [4].

3.3.3: Elliptical Boundary Model

Lee and Yoo [47] proposed an 'elliptical boundary model' in which the skin distribution in chrominance plane can be well approximated by an ellipse. Duo to asymmetry of the skin cluster with respect to its density peak, usage of the symmetry Gaussian model leads to high FPR. It gives superior detection results on the Compaq data set [13], compared to both single and mixture of Gaussians. The elliptical boundary model is defined as

$$\phi(c) = (c-\phi)^T \Lambda^{-1} (c-\phi) \quad (23)$$

Where c is the color vector, Φ and Λ are the model parameters defined as

$$\phi = \frac{1}{n}\sum_{i=1}^{n} ci, \qquad \Lambda = \frac{1}{N}\sum_{i=1}^{n} fi\,(ci-\mu)(ci-\mu)^T \quad (24)$$

Where N is the total no. of samples in the training data set , fi is the no. of samples with chrominance ci and μ is the mean of the chrominance vectors in the training data set. Pixel with color c is classified as skin in case Φ(c) <ɵ where ɵ is a threshold value. This model is performed slightly better than that of GMM. However the drawback of this model is that its usage is limited to binary classification.

4. Performance Evaluation

4.1 Color Space Discussion

In color-based skin detection, color space selection seems to be a crucial one. On important question is:' Is there an optimal color space for skin detection?. Only few researches have seriously considered the problem of color space selection and provided justifications for the optimality of their choice. Recent papers on the performance evaluation of color space transformation for skin detection are summarized in table 1.

Different skin types (white, pink ,yellow, brown & dark) under a wide variety of illumination conditions(white , non white, shadows, indoor & outdoor) and different backgrounds should be classified by a good skin classifier. In the above table the performance of the classifiers are evaluated using True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (TPR), and False Negative Rate (FNR).

Different data sets are used by different authors according to their applications. Most of the authors used Compaq and ECU skin and non skin data sets. Compaq data set consists of 13460 color images collected from www. Out of these, 4675 color images contain skin pixels; remaining 8965 images do not contain skin pixels. These images contain skin pixels belonging to persons of different origins and with unconstrained illumination and background conditions. The ECU database consists of 4000 color images. 1% of images were taken with digital camera and the rest were collected manually from the web. The lightening with varied background and the skin types include whitish, brownish, yellowish and darkish skins.

4.2: Normal Skin Detection discussion

Table 2 summarizes each study with the color space transformation used, the classification method used, and the true and false positives (TP & FP). Although different methods use slightly different training and testing image subsets and employ different learning strategies, the table 2 provides an overall picture of the method's performance. In explicit thresholding method, decision boundaries are determined from the skin color of the images. The YIQ color space which is used by Brand & Mason [12], the thresholding of I axis has a detection of 94.7 on Compaq database. In YCbCr, the Phung et al [17] reported that it has a detection rate of 82 on ECU data base. This method has the advantage of its simplicity and speed. But the defined threshold value differs from one color space to other and also one illumination to another. It is very difficult to define a fixed range for different skin color. It is less effective use of shadows and situations where the skin color is not distinguishable from background.

Cheddad [35] proposed an empirical rule based on GMM with EM. He tested his new method on different RGB images with different background and foreground complexities as well as exposing uneven transition in illumination. This method gives least false negative pixels compared with Hsu, Berens et al and P.Peer et al. The main advantage of Cheddad's method is the reduction of dimensionality from 3D to 1D which is contributed enormously to the algorithm's speed.

Li Zhengming et al [48] proposed a new technique to overcome the time consumption which can be applied in a real time system. In this technique set of pixels is skipped and the remaining pixels will be labeled as skin and non skin pixels by using rg color space and the elliptical model (due to the efficiency of Hsu's method) The performance of the histogram technique is degraded due to the presence of overlap between the skin and non skin classes. The detection rate of this technique is slightly higher than the detection rate of GMM. However a very large data set is needed for good classification rate. Large storage is also needed.

Farhad Dadgoster et al [37] proposed a skin classifier based on the Hue histogram of skin pixels. This algorithm has an improvement in comparison with the static skin detection method. This system needs an initial training with a small number of samples. It is also called as Global Skin Detector (GSD). GSD can detect the actual skin pixels with reasonable detection rate. Lee & Yoo [47] compared the performance of SGM and GMM with Elliptical boundary model. All are giving the same TPR of 90% in Compaq data set. In Phung et al's [17] method, the performance of Multilayer Perceptron (MLP) is compared with

Bayseian, Gaussian and explicit thresholding on ECU data set. All are giving similar performance than Gaussian. However GMMs have been a popular choice for skin color segmentation with less training data.

2D Gaussian with Neural network is proposed by Guoliang Yang et al [33] They reported that the detection rate (96%) of this method is more than the other's proposal. Fu et al [19] proposed multidimensional histograms with EM. Training time is reduced more by using this method. Jones and Rehg [13] spent about 24 hours to train the skin and non skin GMMs. By using multidimensional histogram technique, the time taken is only 250s.

From table 1 , we got that the type of the training data base have a direct impact on the classifier performance. Generally the training time is ignored by many researches. However, it may be important for real time applications that require on line training on different data set. So we can consider the type of the training set and test sets used. So the evaluation criteria are dependent on the purpose of the classifier. Suppose the classifier is used as a pre processing step in face detection, high true positives is preferred at the expense of high false positives. In other case, the classifier alone is used to identify faces, then both high TPR and low FPR is very important.

Table 1. Performance Evaluation on Color Spaces

Authors	Color Space	Intensity Comp.	Skin Detection Method	Diff. skin types	TPR	FPR
Yang & Ahuja,99	Luv	No	GMM(16)	Yes	N/A	N/A
Brand & Mason,00	RGB YIQ RGB	Yes	Bayes SPM I-axis Threshold Threshold ratios	Yes	93.4 **94.7** **94.7**	19.8 30.2 32.3
Signal,00	HSV	Yes	Max. likelihood estimation	Yes		
Brown et al ,01	TSL	No	SOM	Yes	78	32
Jones & Rehg,02	RGB RGB	Yes	Bayes GMM(16)	Yes	90 90	14.2 15.5
Lee & Yoo,02	Xyz YCbCr YIQ	No	Elliptical Boundary Model SGM GMM(16)	Yes	90 90 90	20.9 33.3 32.3
Jedyak et al,03	RGB	Yes	Max. Entropy model	Yes	82.9	10
Sebe & Huang,04	Rgb	No	BN	Yes	**99.4**	10
Jeyaram et al,04	SCT SCT	Yes	Bayes SGM	Yes	**98.2** 94.4	N/A N/A
Phung et al,05	YCbCr RGB RGB YCbCr YCbCr	Yes	Thresholding Bayes MLP SGM GMM	Yes	82 88.9 88.5 88 85.2	18.7 10 10 10 10
Farhad Dadgostar ,06	Hue	Yes	Thresholding	N/R	N/A	N/A
Cheddad et al,09	1D RGB	Yes	Gaussian with EM	Yes	N/R	N/R
Zhang et al,09	YCgCb+YCgCr	Yes	Thresholding	Yes	92.1	6
Jouglas et al,09	HSV+rgb+TSL	No	Explicit Thresholding	Yes	N/R	N/R
Li Zhengming,10	Rg	No	Elliptical model +Skipping method	Yes	N/R	N/R
Guoliang Yang et al,10	YCbCr	No	2D Gaussian Model + BN NN	Yes	**96**	15

5. CONCLUSION

In this paper, up to date techniques of color based skin tone detection is presented. A good classifier must be able to discriminate between skin and non skin pixels for a wide range of people with different skin types such as white, yellow, brown and dark. To improve the performance of the classifier, skin color information along with other features such as shape, spatial and motion information can also be used. In real time applications, meeting computational and storage requirements is extremely important.

From this survey , it is concluded that if skin detection is the pre process then Cheddad's [35] approach is the best choice. Otherwise hybrid skin detection which is proposed by Jouglas et al [39] , Zhang et al [38] etc. is the appropriate method.Goodness of color space depends on skin/non skin overlap, skin cluster shape etc regardless of any specific skin segmentation method. Skin segmentation cannot give the impression of how good is the color space suited for skin segmentation because different skin segmentation methods react very differently on color space change

Table 2. Performance On Different Skin Detection Methods

Author's name	Color Spaces used	Test Data base	Evaluation Method	Factors considered in Data set	Best Color space
Zarit,99	CIE LAB,Fleck HS, HSV,nRGB,YCbCr	from web	% correct, skin error	Skin tone, illumination	Fleck HS, HSV
Terrillion,00	Rg,CIExy,TSL,CIE DSH,HSV,YIQ,YES,CIE Lab,CIE Luv	from web	TP/TN	Skin tone, background	TSL
Brand,00	RGB,YIQ	Compaq	TP/FP	N/R	RGB
Albiol,01	HSV,RGB,YCbCr,CbCr	ViBE video data base	ROC	N/R	N/A
Jones et al,02	RGB	Compaq	OC	N/R	-----
Jedynak et al,03	RGB	Compaq	TP/TN	-----	-----
Fu & Yang,04	HSV	ECU	TP/FP	----	----
Phung et al,05	YCbCr,RGB	ECU	TP/FP	Skin tone	RGB
Farhal Dadgostar et al, 06	Hue	From web	TP/TN	----	----
Rosalyn R. Porle et al,09	RGB, rgb, HIS, TSL, SCT, CIE Lab	From web	TP/TN		CIE Lab without Luminence
Cheddad et al,09	RGB	From web	TP	Skin tone,background	1D RGB
Qiag Liu et al,10	HS,YCbCr	From web	N/R	---	N/A
Zhang et al,10	YCgCr+YCgCb	From web	Hit/False rate	Skin with complex backgroud	N/A

N/R- Not Reported, **N/A-Not Applicable**

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