Does Colorspace Transformation Make Any Difference on Skin Detection?

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Abstract

Skin detection is an important process in many of computer vision algorithms. It usually is a process that starts at a pixel-level, and that involves a pre-process of colorspace transformation followed by a classification process. A colorspace transformation is assumed to increase separability between skin and non-skin classes, to increase similarity among different skin tones, and to bring a robust performance under varying illumination conditions, without any sound reasonings. In this work, we examine if the colorspace transformation does bring those benefits by measuring four separability measurements on a large dataset of 805 images with different skin tones and illumination. Surprising results indicate that most of the colorspace transformations do not bring the benefits which have been assumed. [1]

1. Introduction

Skin detection has been gaining popularity and importance in the computer vision community. It is an essential step for the important vision tasks including detection, tracking, and recognition of face and gesture. The process of skin detection generally is a pixel-level process involving a pre-process of colorspace transformation and classiˇcation. Many studies describing skin detection have applied colorspace transformation for the following beneˇts. First, a certain colorspace transformation is assumed to increase the separability between skin and non-skin classes thus improving the classiˇcation process. Second, it is assumed to achieve the illumination invariance. Varying illumination presents additional challenges to the task of skin detection. Some works have dropped the illumination component of the colorspace. Third, it is assumed to group the colors of different skin tones together. However, most works have selected a particular colorspace transformation for their beneˇts with a few or no sound proof.

In order to check which colorspace transformation(s) would bring such beneˇts, we established a sound evaluation framework with the following requirements.

1. **Examining with right statistical measurements.** The colorspace transformation is a pre-process. It should increase the separability between skin and non-skin classes while decreasing the separability among skin tones (since they are all in the same class of skin.) Most of the skin detection methods involve a statistical classiˇcation and we measure four statistical measurements. Two measurements are based on scatter matrices and other two are based on histogram analysis.
2. **Large set of popular colorspace transformations.** We examine eight popular colorspace transformations including normalized RGB, CIE-Lab, HSI, and SCT.
3. **Large and thorough dataset (varying skin tone and illumination conditions).** The dataset must have many samples of skin and non-skin pixels. The skin pixel set must include a large number of different subjects (persons), skin tones, and illumination. We have collected the images with skin pixels from two databases of face images, AR dataset at Purdue and University of Oulo Physics-based Face Database. Our dataset includes 507 images with skin pixels of 197 subjects, taken by two different cameras, ˇve different light types, three different levels of light amount, and three different levels of skin tones. The set of images with non-skin pixels has been collected from the University of Washington's Content-based Image-Retrieval dataset. The entire dataset consists of 59 million pixels.

We attempt to provide the answers to some of popular claims on the effects of colorspace transformations on the task of skin detection.

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2. Previous Works

2.1. Comparative Studies

Recent papers on the performance evaluation of colorspace transformations for skin detection are summarized. Zarit *et al.* [20] compared skin pixel classiˇcation performance of two histogram based skin detection methods, lookup table method and Baysian method. Five colorspaces were considered to measure the performance of skin detection methods. In [19], nine chrominance spaces were compared by the performance of a model based approach with Mahalanobis metrics for the face detection method. Tint-Saturation-Luminance (TSL) performed the best followed by normalized Red-Green (rg) and CIE-xy in TP and FP rate in the human face detection. The performances of skin detection methods were quantitatively assessed in [4]. The skin detection methods experimented in the study are color transformation using the Red-Green (RG) ratio, linear color transformation of RGB into YI'Q' colorspace and skin probability map with RGB colorspace.

2.2. Skin Detection Studies

This section describes related skin detection studies. Brown *et al.* [5] used 2D intensity invariant vectors from each colorspace transformations to train the Self-Organizing Map (SOM) model. For each of color transformations, 2D "intensity invariant" vectors were extracted and used to train the SOM model. Hsu *et al.* [9] used YCbCr colorspace transformation to detect skin pixels in the normalized color appearance using "reference white". Skin color was modeled using the Gaussian distribution, then detected by computing Mahalanobis distance. Jones et al. proposed skin / non-skin models based on distributions in RGB space for skin detection. A skin pixel classiˇer is devised through likelihood ratio approach, and a prior probability was determined based on threshold values *et al.* [10]. Saber and Tekalp used YES colorspace transformation to reduce the variations in chrominance caused by luminance for face detection task [16]. Mean vector and covariance matrices were estimated for skin classiˇcation in the combination of a universal threshold value obtained by ROC analysis in the training phase. Sigal *et al.* [17] computed the distribution of skin color using Markov model with adaptive color histogram. The prediction of colorspace distribution is performed by modeling evolution of the color distributions over time using a second-order Markov process. Skin pixels in images was manually extracted and labeled into three levels (skin, non-skin and don't-care) which is similar to the pixel labels used in our ground truth. Garcia and Tziritas [8] ˇrst quantized the HSV colorspace with K-Means algorithm to reduce a number of color clusters. Two subspaces in each YCbCr and HSV with bounding plane equations to assign a given pixel to skin or non-skin label. Oliver *et al.* [13] used spatial coordinates in addition to the normalized RG to obtain blobs as a low level image feature. By estimating mean vector and covariance matrix for 2D and 3D blobs, Gaussian mixture models of skin data were obtained in the colorspace. Fleck *et al.* [7] presented a skin-detection method to report if images contain the naked people using skin ˇlter. The *log*-transformed colorspaces from RGB have been used. The skin ˇlter is created through *log*-opponent based color representation and texture amplitude in green channel to distinguish between skin and non-skin pixels.

3 Experimental Methods

3.1 Color Space Transformations

Color of a pixel in image is deˇned as $[C_0, C_1, C_2]$. The colorspace transformation is a function that converts $[C_0, C_1, C_2]$ to $[C'_0, C'_1, C'_2]$. All images are captured in the Red, Green, Blue (RGB) space. We have evaluated eight colorspace transformations : NRGB (normalized RGB), CIEXYZ, CIELAB, HSI, SCT (Spherical Coordinate Transform) [14], YCbCr, YIQ, and YUV. The RGB is used as a baseline performance. Frequently, the illumination component of the colorspace was dropped to make the skin detection illumination independent. For each colorspace, we dropped its illumination component to form 2D color.

Note that values of each component in $[R, G, B]$ are in the range of $[0, 255]$ and $[r, g, b]$ (lower-cased) in $[0, 1]$. The equations below might not yield the values in $[0, 255]$. The values are adjusted so that it ranges from $[0, 255]$, and they are quantized in 256 levels.

3.2 Dataset

We have collected a total of 805 images of which 507 images contain skin pixels and 298 does not contain skin pixels.

The skin images are from AR face dataset [12] and UOPB face dataset [11]. The non-skin images are collected from University of Washington's content-based image retrieval database [1]. AR face dataset includes more than 4,000 frontal color images of 70 men and 56 women. The dataset varied facial expressions, illumination conditions of (no additional light, additional left light, additional right light, additional two lights) and occlusions. The images were taken at two different times apart by 14 days. No restriction on the appearance (such as make-up, hair style and glasses) was placed. UOPB dataset includes 2,112 frontal images of 111 different people in 16 camera calibration and illumination conditions of horizon, incandescent, uorescent and daylight.

3.3 Ground Truth

Figure 1. Sample of GT images. Skin pixels are colored in black. Difficult and tedious regions to mark ('don't care') are colored in gray. The background in the skin images is also marked in gray indicating that those pixels did not participate in the evaluation.

The ground truth (GT) is deˇned at pixel-level. We adopt the three labels method as shown in [3] where each pixel is labeled as skin (black), non-skin (white), or don't-care (gray). `Don't care' label is assigned to pixels that are too ambiguous to mark either way or too tedious to mark skin or non-skin pixels. Since it is difˇcult to accurately mark the boundary pixels between skin and non-skin regions, we label the boundary pixels width of 5 pixels as don't care. The ground truthers were asked to spend at least 15 minutes on each image and to start from the most obvious regions. Figure 1 shows a sample GT of skin image. Since the background of the skin images was mostly white, we did not use the pixels of the background as non-skin data. The background pixels of skin images are labeled as gray indicating that they were not used for the experiments. For non-skin images, the entire image is marked as white (non-skin.)

3.4 Performance Metrics

We compare clusters of skin and non-skin samples using four metrics. $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ and $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ are based on scatter matrix. The histogram intersection (**HI**) and the histogram χ^2 error (**HCE**) are based on the histogram analysis.

The number of samples in two clusters of skin and non-skin is close but not identical. And we have noted that $tr[\mathbf{S}_W]$ monotonically increases when more samples added into the clusters. We have normalized the metrics so they are not variant to the number of samples.

3.4.1 Scatter Matrix based Metrics

We compute the separability of clusters of skin and non-skin pixels by computing following scatter matrices. $\mathbf{S}_W$ computes the scatterness within cluster while $\mathbf{S}_B$ computes the scatterness between clusters [6]. The dataset contains d-dimensional samples $\mathbf{x} = [x_1, x_2, ..., x_d]$, of c clusters. Each cluster (D_i) contains n_i samples with the total of n samples. Thee mean vector of each cluster $(\mathbf{m}_i)$ and the total mean vector $(\mathbf{m})$ are deˇned as

$$\mathbf{m}_i = \frac{1}{n_i}\sum_{\mathbf{x}\in D_i}\mathbf{x} \qquad \mathbf{m} = \frac{1}{n}\sum_{D}\mathbf{x} = \frac{1}{n}\sum_{i=1}^{c} n_i\mathbf{m}_i$$

The scatter matrix for the ith cluster $(\mathbf{S}_i)$ and its normalized value $(\mathbf{S}'_i)$ are computed

$$\mathbf{S}_i = \sum_{\mathbf{x}\in D_i}(\mathbf{x}-\mathbf{m}_i)(\mathbf{x}-\mathbf{m}_i)^t \qquad \mathbf{S}'_i = \frac{1}{n_i}\mathbf{S}_i$$

The normalized within-cluster scatter matrix $(\mathbf{S}'_W)$ and the normalized between-cluster scatter matrix $(\mathbf{S}'_B)$ are computed as

$$\mathbf{S}'_W = \sum_{i=1}^{c}\mathbf{S}'_i \qquad \mathbf{S}'_B = \sum_{i=1}^{c}(\mathbf{m}_i-\mathbf{m})(\mathbf{m}_i-\mathbf{m})^t$$

Tighter clusters (with smaller $\mathbf{S}_w$) that are far separated (with larger $\mathbf{S}_b$) are preferred for easier classiˇcation. We compute two scalar measurements using the scatter matrices. First, $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ computes the ratio between traces of $\mathbf{S}_W$ and $\mathbf{S}_B$. Second, $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ compute the invariant measurements as it is also deˇned as

$$tr[\mathbf{S}_W^{-1}\mathbf{S}_B] = \sum_{i=1}^{d}\lambda_i$$

where $\lambda_1, ..., \lambda_d$ are the eigenvalues of $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$.

3.4.2 Histogram Comparison

Two histograms for colors of skin $(\mathbf{H}_S)$ and non-skin $(\mathbf{H}_{NS})$ pixels after a colorspace transform are computed. The histograms are created at the resolution of 256x256x256 for 3D colorspaces and 256x256 for 2D colorspaces.

HI the similarity between two histograms. Let b be the number of bins in the histograms and each bin can be addressed by index of j as $\mathbf{H}(j)$. We normalized $\mathbf{H}(j)$ as

$$\mathbf{H}(j)' = \frac{1}{n}\mathbf{H}(j)$$

Two metrics are computed as following [15, 18].

$$\mathbf{HI} = \sum_{j=1}^{b} min(\mathbf{H}_S(j), \mathbf{H}_{NS}(j)) \tag{1}$$

$$\mathbf{HCE} = \sum_{j=1}^{b}\frac{(\mathbf{H}_S(j)-\mathbf{H}_{NS}(j))^2}{\mathbf{H}_S(j)+\mathbf{H}_{NS}(j)} \tag{2}$$

4 Results

4.1 Overview

In this section, we attempted to answer following three questions by analyzing the results of nine colorspaces. We call colorspaces other than the RGB as *non-RGB*. The color of pixels are originally represented in the RGB space. So, transformation of colorspace to a non-RGB colorspace is considered to be an *additional.* step. In this paper, the *colorspace tranformation* is deˇned as converting the color from the RGB colorspace to a non-RGB colorspace. To check if the *colorspace transformation* does improve the separability thus improving the skin detection performance, the separability measurements of the non-RGB colorspaces are compared against the RGB which is considered as the baseline performance.

The illumination component of a colorspace has been frequently eliminated with the belief that such process will bring the illumination invariance thus improving the skin detection performance under various lighting conditions. To examine such belief, we have examined each colorspace in two *dimensions*: 2D and 3D. All colorspaces in this study represent color in 3D. The 2D representation is obtained by eliminating the dimension of illumination. This yields 18 *colorspace settings* from the combinations of 9 colorspaces in 2 dimensions.

As mentioned in previous section, four metrics (two scatter matrix based and two histogram based) are computed for each colorspace setting yielding 4 (metrics) x 18 colorspace settings = 72 values to analyze. For better separability, lower $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ and **HI**, and higher $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ and **HCE** are desirable. Note that four different metrics could lead to different conclusions. We have used multiple metrics so that the conclusion is not depended on a single evaluation function. We attempt to answer the following three questions. Questions are answered in following subsections.

Table 1. Performance of All Colorspaces in 2D and 3D.

color space	$\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ 2D	3D	$tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ 2D	3D	HI 2D	3D	HCE 2D	3D
CIELAB	4.82	5.35	0.34	0.35	0.12	0.05	1.64	1.86
CIEXYZ	12.02	17.27	1.09	1.20	0.14	0.05	1.60	1.85
HSI	1.91	3.03	1.05	1.12	0.11	0.04	1.67	1.88
NRGB	1.52	1.44	0.89	0.98	0.12	0.11	1.65	1.67
SCT	1.38	5.32	1.10	1.14	0.11	0.04	1.66	1.89
YCbCr	1.19	12.96	1.06	1.20	0.17	0.05	1.51	1.84
YIQ	1.20	15.36	1.06	1.20	0.16	0.05	1.52	1.85
YUV	1.19	12.96	1.06	1.20	0.17	0.05	1.51	1.84
RGB	34.15	12.37	0.86	1.20	0.11	0.03	1.67	1.90
mean	6.60	9.56	0.95	1.06	0.13	0.05	1.60	1.84

4.2 Does colorspace transform help?

The color transformations that are helpful for the task of skin detection should have metrics better than the baseline performance. We compared the performance of the *non-RGB* colorspaces against the baseline performance of the RGB. Four metrics are used for comparison separately for 2D and 3D yielding eight conclusions on the effectiveness of colorspace transform.

Table 1 lists the performance of all colorspaces in 2D and 3D in all metrics. The number of non-RGB colorspace settings that performed better than the RGB for each metric each dimension are listed below. The maximum is eight corresponding to the number of non-RGB colorspaces.

- $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$: 8 in 2D, 4 in 3D
- $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ 7 in 2D, 0 in 3D
- **HI** 0 in 2D, 0 in 3D
- **HCE** 1 in 2D, 0 in 3D.

Note that the observations from four metrics in 2D and 3D were not identical. However, in four out of eight observations, none of colorspace transformations was better than the RGB. In one observation (**HCE** 2D), only the HSI was better than the RGB. This reveals that in histogram-based separability measurements (**HI** and **HCE**), the improvement in separability was minimal.

For the metrics based on scatter matrix, the results were not less consistent. The number of better non-RGB colorspaces were zero in $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ - 3D, four in $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ - 3D, seven in $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ - 2D, eight in $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ - 2D. In 3D, the color transformations did not provide much improvement. The numbers were higher in 2D than 3D in both scatter matrix based metrics indicating that the improvement is more apparent when the illumination component is eliminated.

Overall, the improvement due to colorspace transformations was visible in 2D of scatter matrix based metrics. However, in other metrics especially the histogram based metrics, the improvement was nearly minimal.

4.3 Does dropping illumination help?

For each metric, there are nine pairs of 2D and 3D performances. We performed the pair-T statistical analysis on four sets of nine pairs to check if the performance of dropping illumination (2D) is statistically better than the 3D space (refer to Table 2.)

For **HI** and **HCE**, keeping illumination (3D) is statistically better than dropping the illumination (2D) within 95% conˇdence interval. For $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$, 3D is better than 2D

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Table 2. Paired Samples T-Test on 3D and 2D (illumination dropped) for each metric.

	paired differences							
				95% conf interv of the diff				
	mean	std. dev	std. error mean	lower	upper	t	df	sig (2-tailed)
$\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$	-2.96	10.71	3.57	-11.20	5.27	-0.83	8	0.43
$tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$	-0.12	0.10	0.03	-0.19	-0.05	-3.73	8	0.01
HI	0.08	0.03	0.01	0.06	0.11	7.09	8	**0.00**
HCE	-0.24	0.10	0.033	-0.32	-0.16	-7.21	8	**0.00**

within 93% conˇdence interval. The mean differences in $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ were not statistically signiˇcant.

Overall, the 2D (dropping of illumination component) was found to actually **signiˇcantly decrease** the separability in 3 out of 4 measurements with 93% conˇdence.

4.4 What is the best colorspace?

We have 18 colorspace settings from the combinations of 9 colorspaces and 2 dimensions (2D and 3D). By using four metrics, we ranked the colorspaces for the task of skin detection to ˇnd which colorspace setting is most suitable for skin detection.

First, note that the rankings of colorspaces are different for four metrics; the average of standard deviation of rankings among four metrics for a given colorspace was 4.78. Note that the rankings between two scatter matrix based metrics changed much more than between two histogram metrics. The only changes of ranking between **HI** and **HCE** were HSI-2D, NRGB-3D, and RGB-2D. Ranking changes between $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$ and $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ were larger. For instance, RGB-3D was the best in $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$ while being 13th (out of 18) in $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$. In fact, half of colorspaces faced ranking changes of 9 or more.

The best colorspaces are YCbCr-2D ($\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$), RGB-3D for other three measurements. The fact that the RGB-3D was the best colorspace settings in three out of four metrics indicates that (1) the colorspace transformations and (2) the reduction of illumination component (2D) did not improve the performance in the task of skin detection.

The ranking was assessed including RGB so the value ranges from 1 to 9. We treat the performance of RGB as a baseline and all other colorspaces as color transformations. Note that the ranking of RGB colorspace was the ˇrst or the second in ˇve out of eight measurements. For the histogram-based metrics (**HI** and **HCE**), RGB was actually the ˇrst or second performer in both 2D and 3D. The RGB-3D (RGB in 3D) was the best in $tr[\mathbf{S}_W^{-1}\mathbf{S}_B]$, **HI** and **HCE** when the 2D and 3D colorspaces (total of 18) were ranked. However, it was ranked 13th in $\frac{tr[\mathbf{S}_W]}{tr[\mathbf{S}_B]}$. So, most of colorspace transformations did not help on skin detection.

5 Conclusions

Skin detection is an important process in many of computer vision algorithms. A colorspace transformation is assumed to increase separability between skin and non-skin classes, to increase similarity among different skin tones, and to bring a robust performance under varying illumination conditions, without any sound reasonings. In this work, we examined if the colorspace transformation does bring those beneˇts by measuring four separability measurements on a large dataset of 805 images with different skin tones and illumination. We found that the separability between two classes of skin and non-skin was highest in RGB colorspace (or absence of colorspace transformation) according to three of four separability metrics. Dropping of illumination component was found to signiˇcantly worsen the separability in three of four metrics as well.

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