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A Colour Space for Skin Detection Using Principal Components Analysis Technique

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ABSTRACT

Colour is one of the most important features used in skin and face detection. Colour space transformation is widely used by researchers to find better representation of human skin tone. Despite the research efforts in this area, choosing a proper colour space for skin and face detection remained an unsolved issue. Illumination variation, various camera characteristics, different skin colour tones and skin-like colours in background are among major challenges in skin detection. This paper proposes a new colour space based on projection of YCbCr colour space to principal component of three different skin colour clusters corresponding to three human ethnics including Asian, Black and Caucasian by means of a variation of principal component analysis (PCA) technique. Two classifiers including Random Forest and Support Vector Machine (SVM) have been employed to construct the skin colour model. Meanwhile, a dataset of 450 images consist of skin locus of different ethnics (Asian, Black and Caucasian) under various lighting condition was used. The proposed colour space was compared to ten state of the art colour spaces and gave superior results in term of pixel-wised skin classification performance. The experimental results show that the proposed colour space yields F-score rate of 0.9273 and ROC curve area of 0.9563 outperforms other colour spaces in this study.

KEYWORDS: Colour Space, Transformation Matrix, Principal Component Analysis, Skin Detection, Classification.

1 INTRODUCTION

Detecting human skin is an essential technique in numerous computer vision applications such as face detection, human detection, body-part detection, gesture recognition and etc. colours are the most prominent feature of every digital image. Since colour features are invariant against spatial changes like skew, scaling and rotating, they have been used widely for skin detection applications [1]. A colour space is a mathematical representation of the colours, describes the colours as sets of numbers. RGB colour space is the default colour space for most available digital images. High amount of correlation among its components (Red, Green and Blue) and incorporation of the luminance and chrominance are the main drawbacks of the RGB colour space[2]. These drawbacks make RGB an undesirable colour space for image segmentation and retrieval especially in uncontrolled illumination environments[3].

Researchers are trying to find a proper representation of the human skin colour by means of transforming the colours into new spaces. Colour space transformations have applied to the skin detection for the following reasons: first, to increase the reparability between skin and non-skin colours[4]. Second, to reduce the average correlation among different components of colour space [5]. Third, to separate the intensity and chrominance components [4]. Fourth, to increases the likeness and unity of the skin tones of different human ethnics (Black, Caucasian and Asian)[6]. Colour space transformation usually employed as a preprocessing technique in preliminary stage of skin detection[7]. Variety of different models and techniques has been proposed for skin detection but a typical skin detection usually fits in the scheme showed in figure 1 [7].

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Figure. 1. Typical skin detection scheme

Despite the research efforts in this area, choosing a proper colour space for skin and face detection remained an unsolved issue. Illumination variation, various camera characteristics, different skin colour tones and skin-like colours in background are the main challenges in skin detection. During the last decade several colour spaces such as RGB, nRGB, YCbCr, HSI, HSV, CIEXYZ, YUV, YCgCr, TSL and CIELAB have been applied to skin classification. Each of them has its own advantages and drawbacks. Studies shows colour spaces which separate the luminance and chrominance components such as HSV, TSL and YCbCr are likely to be more appropriate for skin detection. Among these colour spaces YCbCr is in the center of attention of many researchers. YCbCr colour space is designed as a digital approach to handle video information in colour television system. It is a very popular colour space for skin and face detection purposes and used by many researcher including [8][9][1][10][11][12][13] for this purpose. following shows the transformation matrix maps the RGB colour space to YCbCr [14]:

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.48 & 128.55 & 24.96 \\ -37.79 & -74.20 & 112 \\ 112 & -93.78 & -18.21 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

This research proposes a new colour space named ABC (Stands for Asian, Black and Caucasian) based on projection of YCbCr colour space to principal component of three different skin colour clusters corresponding to three human ethnics including Asian, Black and Caucasian by means of a variation of PCA (principal component analysis) technique. This study performs a comparison analysis in term of pixel wised skin detection performance between the proposed colour space and ten other frequently used colour space. We have employed the Random forest and SVM classifier to construct the skin colour model for each colour space. Quantitative results expressed through ROC curve and F-score shows the proposed colour space outperformed other colour spaces in this study in term of pixel-wised skin detection. Qualitative comparison also acknowledges the dominance of the proposed colour space. The remaining of this paper is as follow: section 2 goes through the related works, section 3 presents the dataset and ground truth setup, section 4 presents the methodology, section 5 describes the results and analysis and finally section 6 brings a conclusion to this study.

2 RELATED WORKS

However some researchers believe that colour space transformation does not make any significant enhancement in skin detection [4][15] but recent researches reveals the importance of the colour space for skin detection applications. There are lots studies that focused on colour space transformation to improve pixel wised skin detection performance. De dios et al. [16][17] proposed YCgCr colour space, to enhance face detection experience. This colour space is based on YCbCr but unlike that it uses the smallest colour difference (G-Y) instead of (B-Y). They have claimed this technique enhances the face detection performance. In another study, Queisser [18] proposed a new colour space named βδε which is optimized for uniformly coloured object segmentation. β is the primary axes, reflects the principal component of the object colours while δ and ε are distance and angel that each colour makes with the primary axis respectively. Their proposed colour space claimed to have lesser cross-correlation compare to RGB colour space. Hosseini et al. [19] used a convex constraint quadratic optimization technique to find the linear transformation matrix which yields a skin detection optimized colour space. It was claimed that their proposed colour space delivered superior results compare to traditional colour spaces.

Jones and Abbott [20] presents an optimized the colour space transformation for face recognition using three approaches including Karhunen-Loeve (PCA) transformation, linear regression of skin colour distribution and genetic algorithms. It is claimed that these approaches deliver overall improved performance. Yihuashi et al. [21] proposed a space transformation by using an adaptive gamma correction method. They used a non-linear conformal mapping technique to establish a relationship between gamma and pixel value. It is claimed that this approach enhanced skin colour detection performance. Khan et al. [1], Schmugge et al. [9] ,Terrillon et al.[22] and Zarit el al. [6] conducted comparative analysis between existing colour spaces to explore the effects of colour space transformation on pixel-wised skin detection performance. Issues like diversity of skin colour in different ethnics (Asian, African and Caucasian), illumination variation and camera sensor characteristics might have significant negative effects on pixel wised skin detection performance. Despite the efforts of researchers to initiate and adopt a domain specific colour space for the sake of skin detection, lack of a comprehensive solution to respond to these issues is tangible.

3 Dataset and Ground Truth

This study benefits an in house dataset including total number of 450 colour images is prepared through various Internet image resources. It contains overall 54 million pixels where around 15 million of them represent the human skin colour denote the positive instances (skin class) while the rest of the pixels which occupies the images background resemble the negative instances (non-skin class). In term of contents, images are either pornographic or they are exposing substantial amount of human skin patches from different ethnicity, gender and lighting condition (indoor and outdoor). Our dataset divided into of 3 sub-dataset including Asians, Blacks and Caucasians. Each sub-dataset contains 150 images in which 100 of them are used for training and 50 are reserved for testing purposes. In order to increase the reliability of our experiments, the ground truth has been constructed manually at pixel level by means of image editor tools. The ground truth is formed as a mask of skin patches in black background. Any pixel in images which does not represent the skin patch including hair, eyes, lips, spectacles, clothing, tattoo and any background object have been blacked out in ground truth. Figure 2 illustrates some examples of our dataset images and their corresponding ground truth.

Figure. 2. Sample images and corresponding ground truth in dataset

4 METHODOLOGY

Since RGB is a fundamental and commonly used colour space for most of available digital images other colour spaces are expressed through RGB colour space by either a linear or nonlinear transformations. Non-linear colour spaces transformations usually denotes by polynomial or simultaneous equations while linear colour space transformation can be expressed through an associated transformation 3*3 matrix. A typical linear colour space transformation matrix is as follows:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} * \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix} = \begin{bmatrix} A \\ B \\ C \end{bmatrix}$$

Linear colour space transformations are considerably faster than non-linear ones, hence the proposed colour space in study created through a linear transformation. Meanwhile, YCbCr chose as the base of our colour space transformation for two main reasons. First it separates the luminance and chrominance components and second, many literatures come to an agreement about its dominance over other many existing colour spaces in pixel wised skin detection. Figure 3 illustrates the bock diagram of the proposed colour space.

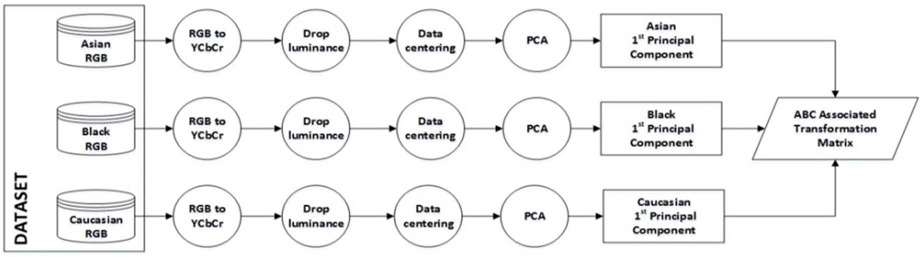

Figure. 3. Block diagram of the proposed colour space for skin detection

The following phases are employed to construct the ABC colour space associated transformation matrix. In the first phases, RGB images in our three sub datasets (Asian, Black and Caucasian) transformed into the YCbCr colour space. YCbCr colour space dedicates an independent component "Y" to luminance. YCbCr images passing through a luminance withdrawal phases, leaving us with a CbCr chrominance plane. CbCr plane features less fluctuation against illumination variation. This may enhance the skin detection performance under uncontrolled illumination environments. The next phases centers data in CbCr plane through a mean subtraction technique. Data centering is commonly practiced as a preliminary process for performing PCA. It ensures that the 1st principal component represents the direction of maximum variance. Mean subtraction process applies to both Cb and Cr components as shown in the following formula. Where $\overline{C_b}$ and $\overline{C_r}$ are the mean of Cb and Cr components respectively. n denotes the total number of instances in each components and cb and cr are the mean centered components.

$$c_b = \sum_{i=1}^{n} (C_{b\,i} - \overline{C_b}) \quad c_r = \sum_{i=1}^{n} (C_{r\,i} - \overline{C_r})$$

In the next phase PCA technique applied into the centered data. PCA is a statistical technique in which mainly used for the data dimension reduction. This phase returns the first principal component in which has the largest possible variance of data in CbCr plane. The last phase joints the first principal components of each sub datasets into the one 3*3 matrix, yields the associated transformation matrix of the ABC colour space as follow:

$$\begin{bmatrix} 0.999 & 0.0107 & -0.0438 \\ 0.0391 & -0.690 & 0.7224 \\ 0.0225 & 0.7234 & 0.690 \end{bmatrix}$$

YCbCr colour space transformation can be bypassed through multiplication of our ABC and YCbCr transformation matrix. Keep in mind that the multiplication order is critical. Following equation shows the transformation matrix that maps RGB to ABC colour space.

$$\begin{bmatrix} 0.999 & 0.0107 & -0.0438 \\ 0.0391 & -0.690 & 0.7224 \\ 0.0225 & 0.7234 & 0.690 \end{bmatrix} * \begin{bmatrix} 65.48 & 128.55 & 24.96 \\ -37.79 & -74.20 & 112 \\ 112 & -93.78 & -18.21 \end{bmatrix} = \begin{bmatrix} 60.1023 & 131.7376 & 26.9269 \\ 109.5584 & -11.5067 & -89.4977 \\ 51.4235 & -115.4913 & 69.0197 \end{bmatrix}$$

$$\begin{bmatrix} A \\ B \\ C \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 60.1023 & 131.7376 & 26.9269 \\ 109.5584 & -11.5067 & -89.4977 \\ 51.4235 & -115.4913 & 69.0197 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

The next section describes the experimental results and analysis and compares the proposed colour space to ten frequently used colour space in term of pixel wised skin detection performance.

5 RESULTS AND ANALYSIS

This section presents a quantitative and qualitative comparison between the proposed colour space and ten existing colour space including RGB, nRGB, YCbCr, i1i2i3, HSI, YES, HSV, XYZ, YUV and YIQ in term of pixel wised skin detection performance. Random forest and SVM classifiers are employed to generate the skin colour model in each colour space. Random Forest decision tree classifier is a popular classifier in face and skin detection applications and already used by many researchers in this area. The number of trees is an important factor in random forest classifier. The number of trees has been assessed empirically. The highest f-score has been observed when the number of the trees has been set to 12. Lower number of trees decreases the f score while more trees do not make significant improvements in evaluation measures and increase the time complexity of the system. SVM is another frequent used colour space in this area. Its aim is to finds a hyper plane with maximal marginal inter space between the classes. The optimal results have been achieved empirically when we used a degree-3 polynomial to construct the kernel. The Feature vector in these experiments consists of three attributes, resembling the components of the corresponding colour space. This study used 10 fold cross validation technique in order to validate the experiments results. We have relied on F-score as the primary performance measure to evaluate each colour spaces performance in term of pixel wised skin detection. F-score yields through recall and precision values, gives a comprehensive outlook about the performance of each colour space. Table 1 shows the F-score value of ten existing colour space alongside the proposed ABC colour space.

Table 1. F-score value of ten existing colour space alongside the proposed colour space over random forest and SVM classifiers. Significant results are bolded.

Colour Space	Random Forest	SVM
RGB	0.832	0.705
nRGB	0.897	0.818
YCbCr	0.915	0.855
i1i2i3	0.909	0.832
HSI	0.901	0.861
YES	0.834	0.806
HSV	0.891	0.797
XYZ	0.827	0.796
YUV	0.857	0.789
YIQ	0.894	0.848
ABC (Proposed Colour Space)	0.9273	0.8923

Table 1 reveals that the proposed ABC colour space with F-score rate of 0.9273 on Random Forest and 0.8923 on SVM outperformed other colour spaces in term of pixel wised skin detection. Meanwhile, It can be inferred that Random Forest delivered averaging better results than SVM in term of pixel wised skin detection and shown a consistent performance over different colour spaces. Followed by proposed colour space, YCbCr and HSI colour spaces also shown remarkable performance. On the other hand, RGB colour space yields relatively poor performance compare to other colour spaces in this study. High amount of correlation among its components and integration of chrominance and luminance might be the main reasons of RGB poor performance. Figure 4 shows the ROC (receiver operating characteristic) curve of the proposed ABC colour space alongside RGB, YCbCr using Random Forest classifier. ROC curves plots the true positive rate on vertical axis and false positive rate on horizontal axis, visualizes an understandable outlook of performance. The rule of thumb is as we get close to the top left corner the classification performance increases. The proposed ABC colour space encloses 0.9563 under its ROC curve which is considerably greater than 0.9123 and 0.8244 hit by YCbCr and RGB respectively.

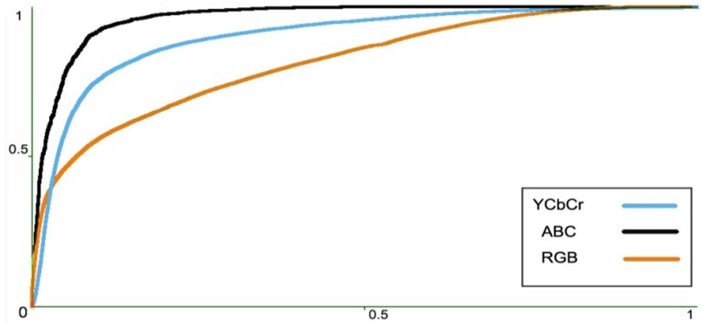

Figure. 4. ROC curves of the proposed ABC colour space alongside the RGB and YCbCr under Random Forest classifier.

Qualitative comparison provides more understandable picture of the proposed colour space performance. Figure 5 presents a qualitative comparison among the ABC, YCbCr and RGB colour spaces. It is include three images, each represent one sub dataset (Asian, Black and Caucasian) of this study. The blue patches resemble the pixels that have been detected as skin. Comparing the results with the Ground truth infers that proposed ABC colour space outperformed YCbCr as well as RGB colour space in term of pixel wised skin detection.

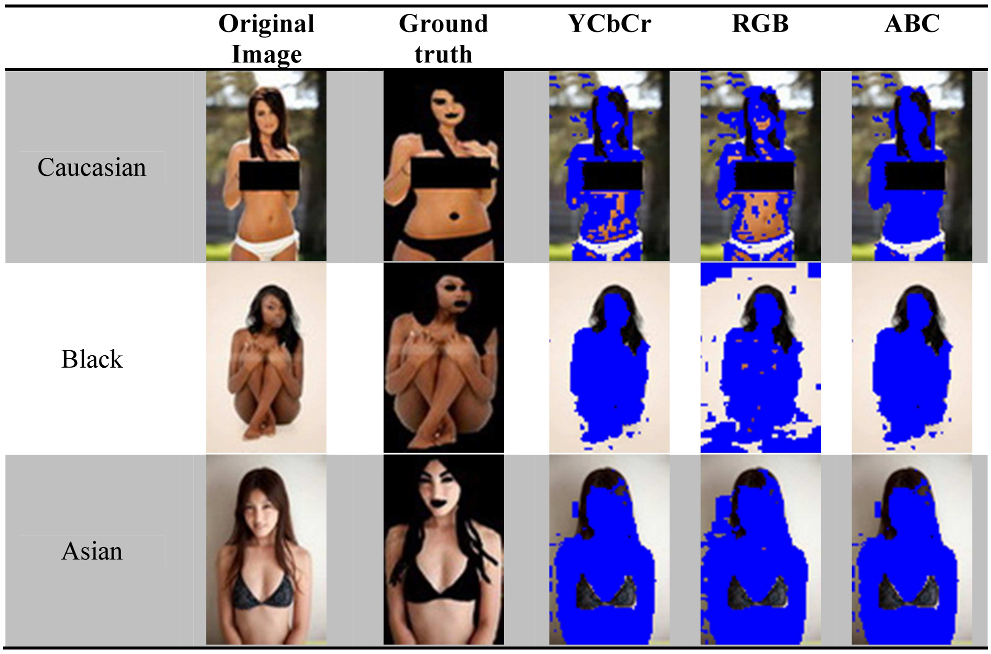

Figure. 5. Qualitative comparison of pixel wised skin detection among RGB, YCbCr and the propose ABC colour space. The blue colour patches resembles the positive results (FP+TP). Ground truth and original image provided as the reference.

6 Conclusion

In this paper we proposed a colour space that improves skin detection performance. It responses to problem of variance of skin tone in different ethnics. The proposed colour space named ABC (Stands for Asian, Black and Caucasian) yields through projection of YCbCrcolour space to principal component of skin colour of three ethnics including Asian, Black and Caucasian by means of a variation of principal component analysis (PCA) technique. Experimental results show that the using proposed colour space we are able to achieve higher amount of skin detection rates.

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