Static Filtered Skin Detection

Rehanullah Khan [1], Zeeshan Khan [2], Muhammad Aamir [1], Syed Qasim Sattar [1]

[1] Sarhad University of Science and Information Technology, Peshawar
[2] University of Engineering and Technology, Peshawar

ABSTRACT

A static skin filter defines explicitly (using a number of rules) the boundaries the skin cluster has in a color space. Single or multiple ranges of threshold values for each color space component are created and the image pixel values falling within these range(s) for all the chosen color components are defined as skin pixels. In this paper, we investigate and evaluate static skin filters for skin segmentation. As a contribution, two new static skin filters for the IHLS and CIELAB color spaces are developed. The two new static filters and four state-of-the-art static filters in YCbCr, HSI, RGB and normalized RGB color spaces are evaluated on the two datasets DS1 and DS2, on the basis of F-measure. Experimental results reveal the feasibility of the developed static skin filters. We also found that since the static filters use static boundaries, any shift of skin color ranges from the static boundaries will result in varying performance. Therefore, the F-measure rankings of the color spaces are different for the datasets DS1 and DS2.

Keywords: Static skin filters, color space thresholding

1. INTRODUCTION

Locating and tracking patches of skin-colored pixels through an image is a tool used in many face recognition and gesture tracking systems [19][9]. Skin information contributes much to object recognition [24]. One of the usage of skin color based tracking, locating and categorization could be blocking unwanted video contents on World Wide Web [10]. On dedicated websites, people can upload videos and share it with the rest of the world. There are uploaded adult videos, which may not be allowed by the service providers. Therefore, how to effectively categorize and block such videos in real-time has been arousing a serious concern for the service providers. The advantage of static filters is the simplicity of skin detection rules. This results in the construction of a classifier which is computationally favorable [21]. For the static filters, we need to find both a good color space and adequate decision rules empirically. Generally, the true positive rate can be increased by tuning but at the same time the false positive rate is also affected [5, 7, 11].

In this paper, we investigate and evaluate static skin filters. As a contribution, we introduce two new static skin filters in the IHLS and CIELAB color spaces. The two new static filters and four state-of-the-art static filters in YCbCr, HSI, RGB and normalized RGB color spaces are evaluated on the two datasets DS1 and DS2, on the basis of F-measure. Experimental results reveal the feasibility of the developed static skin filters.

Singh et al. [19] presents a detailed discussion on various color spaces and skin detection techniques. In their work, they mainly consider three color spaces; RGB, YCbCr and HSI. They have compared various algorithms based on these color spaces and have combined them for face detection. However, the algorithm fails when sufficient non face skin is visible in the images. In [21], the effect of using various color spaces in skin detection is discussed. In addition, the authors state that excluding color luminance from the classification process cannot help achieving better discrimination between the skin and non skin areas/pixels in the image.

In [25] and [26], skin information based image filters are described. The first step in their approach is skin detection. The distribution of skinness in the input image is modeled using the Maximum entropy modeling. Then, a first order model is built that introduces constraints on color gradients of neighboring pixels. The output of the skin detection step is a gray scale skin map with the gray levels being proportional to the skinness probabilities. False alarms are raised in the skin detection process when the background color matches the human skin color. According to [2], using two or more color spaces shows better performance in comparison to a single color space which may limit the performance of the skin color filter.

Jae et al. [12] discuss elliptical boundary model for skin color detection. They investigate the characteristics of skin and non-skin distributions in terms of chrominance histograms to devise an appropriate model for skin detection and don't employ the method of combining different color spaces. In [22], a method to detect body parts in images is presented. The algorithm presented in this work is composed of both content-based and image-based classification approaches. In the content-based approach, color filtering and texture analysis is used to detect the skin region in an image and its classification depends on the presence of large skin bulks. In the image-based approach, color histogram and coherence vectors are extracted to represent the color and spatial information of the image.

According to [13] and [15], the quality of skin color modeling is influenced by the selection of color space. The pixels belonging to skin region in all human races exhibit similar Cb and Cr chromatic characteristics, therefore the skin color model based on Cb and Cr values cover almost all human races. Accordingly, despite their different appearances, these color types belong to the same small cluster in Cb-Cr plane. A typical viewer perceives a difference in skin colors mainly based on the darkness or fairness of the skin. These features are reflected as a difference in the brightness of the color, which is governed by Y component rather than Cb and Cr components. It provides an effective separation into luminance and chrominance channel and generates a compact skin chroma distribution. Yang et al. [24] have introduced a new Gamma Correction method to reduce the effects of illumination on images. They have also introduced a new RGB non-linear transformation to describe the skin and non-skin distributions. Khan et al. [11][5][7] use face detection for adapting to the varying illumination conditions for detecting skin in videos. The authors in [6] introduce the usage of Decision Trees for pixel based skin detection and classification. A global seeds based skin detection method is introduced in [8].

Color is a low level feature, which makes its usage computationally inexpensive and therefore suitable for real-time object characterization, detection and localization [13]. The major aim of skin color detection or classification for skin contents filtering is to establish a decision criterion that will discriminate between skin and non-skin pixels in an image. Identifying skin colored pixels in a given color space involves finding the range of values which most skin pixels would possess. This may be as simple as classifying a pixel as skin pixel based on its association to an explicit set or range of values of Red, Green and Blue color channels' distribution. On the other hand, a range of complex prediction techniques can be employed which use Neural Networks and Bayesian methods [13].

The rest of the paper is organized as follows: Section 2 explains in detail the four state-of-the-art static filters and the two new static filters developed. Section 3 explains the datasets and an evaluation and Section 4 concludes.

2. COLOR SPACE THRESHOLDING

Human skin color can be approximated in a well defined cluster given a color space, if the recording conditions for the images remain consistent (illumination controlled environment)[23]. Based on this idea, one method is to build a static skin classifier. A static skin classifier defines explicitly (using a number of rules) the boundaries the skin cluster has in a color space. Single or multiple ranges of threshold values for each color space component are created and the image pixel values falling within these range(s) for all the chosen color components are defined as skin pixels. The advantage of this method is the simplicity of skin detection rules and the computational efficiency because it is pixel based. The main difficulty achieving high recognition rates with this method is the need to find both a good color space and adequate decision rules empirically [21]. Generally, the True Positive (TP) rate is high but at the same time due to the large boundary of the static filter, the False Positive (FP) rate is also high.

Chai and Ngan [1] exploit the spatial distribution of human skin color in images. A static skin filter is derived and uses the chrominance components of the image for skin pixel detection. It is assumed that the different skin colors that are perceived in the image cannot be differentiated by the chrominance information of the corresponding image region and therefore, skin color can be represented by the static values of Cb and Cr component of the YCbCr color space. The ranges for the static filters are found by testing on a large number of images and then tuning the corresponding values in case of violations. The final values reported are,

$$Cb_{max} = 127,\ Cb_{min} = 77,\ Cr_{max} = 173,\ Cr_{min} = 133 \tag{1}$$

A pixel is skin, if it lies between these values.

Peer et al. [16] advocate the usage of the RGB color space for face detection. They specifically deal with the problem of varying illumination and compensate for lighting correction using the Gray World algorithm and Color by Correlation technique. Classification of skin color is performed by heuristic rules taking into account two different illumination conditions: Uniform daylight and lateral illumination. A filter for uniform daylight illumination is:

$$R > 95, G > 40, B > 20 \tag{2}$$

$$(Max\{R,\ G, B\} - \min\{R, G, B\}) > 15$$

$$|R - G| > 15, R > G, R > B$$

A filter for daylight lateral illumination (flashlight) is:

$$R > 220, G > 210, B > 170 \tag{3}$$

$$|R - G| \leq 15, B < R, B < G$$

A static filter for the normalized RGB color space is reported in [3]. The paper describes a new constructive induction algorithm for creating adequate attributes to constitute the skin map. Using a simple set of operators and the three normalized RGB components, a model for skin detection is presented with a combination of different rules. The Restricted Covering Algorithm (RCA) is used for selective learning during the training phase. RCA is based on selection of single well defined separable rules. RCA performs its

Fig. 1. Example frames from the annotated video dataset (DS1).

search in parallel for finding a single set of rules. There are different combinations of rules reported and the highest precision and accuracy is reported for the following rule:

$$\frac{nr}{ng} > 1.185 \quad (4)$$
$$\frac{nr.nb}{(nr + ng + nb)^2} > 0.107$$
$$\frac{nr.ng}{(nr + ng + nb)^2} > 0.112$$

where nr, ng and nb correspond to normalized coordinates. Skin detection is used as a cue for face detection in [17] using the HSI color space. A binary skin map is generated for oriental face detection for locating multiple faces in natural scenes. A clustering-based splitting algorithm is used to separate facial and non-facial regions in the skin color map. The HSI color space is favored because of its stable behavior in non-uniform lighting conditions. Skin is segmented in the HSI color space based on the following rules:

$$I > 40 \quad (5)$$
$$13 < S < 110, 0^\circ < H < 28^\circ \quad \text{Or} \quad 332^\circ < H < 360^\circ$$
$$\text{Or}$$
$$I > 40$$
$$13 < S < 75,\ 309^\circ < H < 331^\circ$$

A static skin filter in the HSV color space is reported in [20]. The authors argue that skin color can be accurately characterized by hue and saturation. The thresholds used in the HSV color space for skin segmentation are:

$$V \geq 40 \quad (6)$$
$$0.2 < S < 0.6;$$
$$0^\circ < H < 25^\circ \quad \text{or} \quad 335^\circ < H < 360^\circ$$

The V component filters out dark colors. The range of saturation S excludes pure red or dark red colors. The hue H and saturation S account for slightly varying lighting conditions.

We developed two new static filters for the IHLS and CIELAB color spaces. For the IHLS color space, we built a static filter from the skin distribution in Weka [4] and refined the corresponding values on test images. Finally, the following rules are adopted:

$$iH_{max} = 50,\ iH_{min} = 0,\ iS_{max} = 0.9,\ iS_{min} = 0.1 \quad (7)$$

where iH_{max} and iH_{min} are the upper and lower boundary values for the hue component, iS_{max} and iS_{min} are the upper and lower boundary values for the saturation component of the IHLS color space. For CIELAB, we also built a static filter using the same procedure as that of the IHLS color space and finally using the following rules:

$$a_{max} = 14,\ a_{min} = 2,\ b_{max} = 18,\ b_{min} = 0.7 \quad (8)$$

3. EVALUATION

In an experimental setup, the two new static filters and four state-of-the-art static filters in YCbCr, HSI, RGB and normalized RGB color spaces are evaluated on the two datasets DS1 and DS2, on the basis of F-measure. The dataset (DS1) is created mainly by Christian Liensberger [14], spanning 25 YouTube videos (see Figure 1). The second dataset (DS2) is provided by Sigal et. al. [18] (see Figure 2).

Fig. 2. Example frames from dataset (DS2) consisting of 21 video sequences. (Source: [18]).

In an evaluation setup, for YCbCr, the static filter reported in [1] is used. For HSI, the static filter of [17] is used. For the RGB color space, the static filter reported in [16] is used. For normalized RGB, static filter of [3] is used. For IHLS and CIELAB color spaces, we use the newly developed static filters.

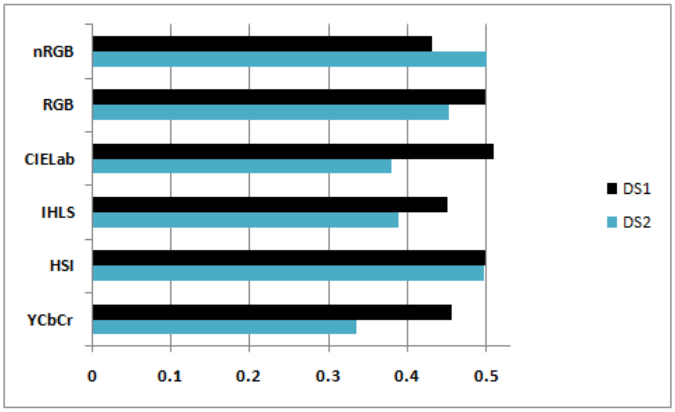


Fig. 4. F-measure for DS1 and DS2 based on static skin filters in six color spaces.

Figure 3 shows the output of these static skin filters on two images. Figure 3 (second row) shows an actor from a movie scene with items having skin like colors. The static filter in the IHLS color space (Figure 3(k)) reports fewer false positives compared to the other five static filters. Figure 4 shows the F-measure for static filters of the six color spaces for datasets DS1 and DS2. For DS1, The highest F-measure of 0.50 is reported by the CIELAB static filter and the lowest F-measure of 0.43 by the normalized RGB. The second highest F-measure of 0.49 for DS1 is reported by the HSI and the RGB static filters. YCbCr achieves an F-measure of 0.45. For the dataset DS2, the highest F-measure of 0.50 is reported by the normalized RGB static filter and the lowest F-measure of 0.33 by YCbCr. The second highest F-measure of 0.49 is reported by the HSI static filter. IHLS, CIELAB and RGB achieve F-measures of 0.38, 0.37 and 0.45 respectively. It can be seen that in Figure 4, varying (non-uniform) performance is reported for different static filters. The two datasets DS1 and DS2 represent skin colors in different lighting conditions, resulting in different skin locus (skin color ranges in a color space) for the corresponding dataset (and color space). Since, the static filters use static boundaries, any shift of skin color ranges from the static boundaries will result in varying performance. Therefore, the F-measure rankings of the color spaces are different for the datasets DS1 and DS2.

4. CONCLUSION

In this paper, we investigated and evaluated six static skin filters for skin segmentation. We introduced two new static skin filters for the IHLS and CIELAB color spaces. The two new static filters and four state-of-the-art static filters in YCbCr, HSI, RGB and normalized RGB color spaces are evaluated on the two datasets DS1 and DS2. Experimental results reveal the feasibility of the developed static skin filters. We also found that since the static filters use static boundaries, any shift of skin color ranges from the static boundaries will result in varying performance. Therefore, the F-measure rankings of the color spaces are different for the datasets DS1 and DS2.

5. REFERENCES

[1] D. Chai and K.N. Ngan. Locating facial region of a head-and-shoulders color image. In Int. Conf. Automatic Face and Gesture Recognition, pages 124–129, 1998.

[2] Moheb R. Girgis, Tarek M. Mahmoud, and Tarek Abd-El-Hafeez. An approach to image extraction and accurate skin detection from web pages. In Proceedings of World Academy of Science, Engineering and Technology, pages 367–375, 2007.

[3] Giovani Gomez and Eduardo F. Morales. Automatic feature construction and a simple rule induction algorithm for skin detection. In ICML, pages 31–38, 2002.

[4] G. Holmes, A. Donkin, and I.H. Witten. Weka: a machine learning workbench. In Second Australian and New Zealand Conference on Information Systems, pages 357–361, nov-2 dec 1994.

[5] Rehanullah Khan, A. Hanbury, and J. Stöttinger. Weighted skin color segmentation and detection using graph cuts. In Proceedings of the 15th Computer Vision Winter Workshop, pages 60–68, February 2010.

[6] Rehanullah Khan, Allan Hanbury, and Julian Stoettinger. Skin detection: A random forest approach. In ICIP, pages 4613 – 4616, 2010.

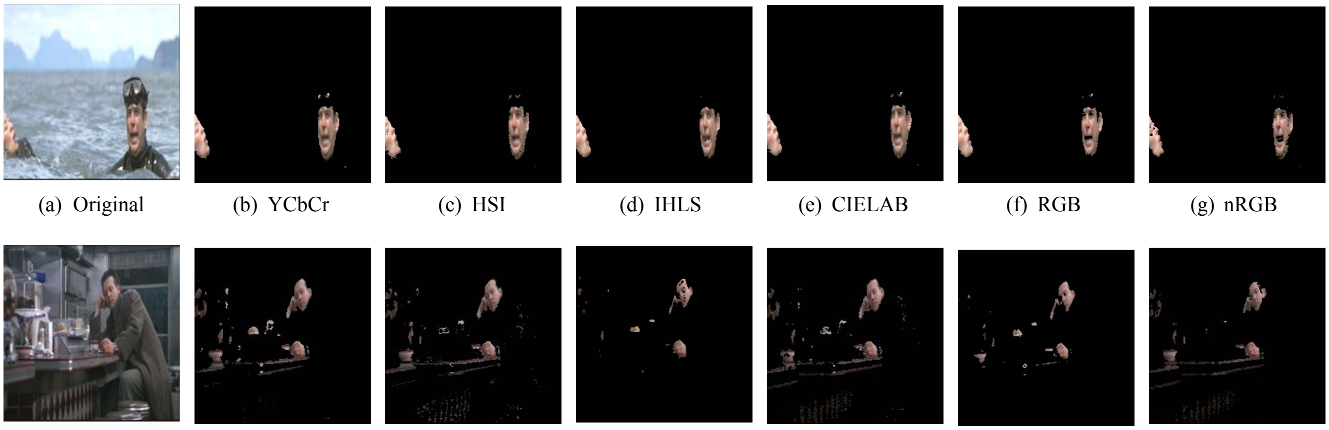
[7] Rehanullah Khan, Allan Hanbury, and Julian Stöttinger. Augmentation of skin segmentation. In International Conference on Image Processing, Computer Vision, and Pattern Recognition, pages 473–479, 2010.

[8] Rehanullah Khan, Allan Hanbury, and Julian Stöttinger. Universal seed skin segmentation. In International Sym- posium on Visual Computing, pages 75–84, 2010.

[9] Rehanullah Khan, Allan Hanbury, Julian Stttinger, and Abdul Bais. Color based skin classification. Pattern Recognition Letters, 33(2):157 – 163, 2012.

[10] Rehanullah Khan, Asad Maqsood, Zeeshan Khan, Muhammad Ishaq, and Arsalan Arif. Skin-color based videos categorization. IJCSI, 9(1):473–477, 2012.

[11] Rehanullah Khan, Julian Stöttinger, and Martin Kampel. An adaptive multiple model approach for fast content-based skin detection in on-line videos. In ACM MM, AREA workshop, pages 89–96, 2008.



(a) Original (b) YCbCr (c) HSI (d) IHLS (e) CIELAB (f) RGB (g) nRGB

(h) Original (i) YCbCr (j) HSI (k) IHLS (l) CIELAB (m) RGB (n) nRGB

Fig. 3. Example results of skin detection using static skin filters in different color spaces. Black shows non-skin.

[12] Jae Young Lee and Suk Yoo. An elliptical boundary model for skin color detection. In ISST, pages 579–584, 2002.

[13] Jiann-Shu Lee, Yung-Ming Kuo, Pau-Choo Chung, and E-Liang Chen. Naked image detection based on adaptive and extensible skin color model. PR, 40(8):2261–2270, 2007.

[14] Christian Liensberger, Julian Stöttinger, and Martin Kampel. Color-based and context-aware skin detection for online video annotation. In MMSP, pages 1–6, 2009.

[15] Yung ming kuo, jiann-shu lee, and pau-choo chung. The naked image detection based on automatic white balance method. In 2006 ICS International Computer Conference, pages 990–994, 2007.

[16] Peter Peer, Jure Kovac, and Franc Solina. Human skin colour clustering for face detection. In EUROCON, pages 144–148, vol.2, 2003.

[17] Hsieh I. Sheen, Fan K. Chin, and Chiunhsiun Lin. A statistic approach to the detection of human faces in color nature scene. PR, 35(7):1583 – 1596, 2002.

[18] L. Sigal, S. Sclaroff, and V. Athitsos. Skin color-based video segmentation under time-varying illumination. PAMI, 26(7):862–877, July 2004.

[19] Sanjay Kr. Singh, D. S. Chauhan, Mayank Vatsa, and Richa Singh. A robust skin color based face detection algorithm. Tamkang Journal of Science and Engineering, 6(4):227–234, 2003.

[20] Sofia Tsekeridou and Ioannis Pitas. Facial feature extraction in frontal views using biometric analogies. In EUSIPCO, pages 315–318, 1998.

[21] Vladimir Vezhnevets, Vassili Sazonov, and Alla Andreev. A survey on pixel-based skin color detection techniques. In GraphiCon, pages 85–92, 2003.

[22] Shilin Wang, Hong Hui1, Sheng hong Li, Hao Zhang, Yong yu Shi, and Wen tao Qu. Exploring content-based and image-based features for nude image detection. In Fuzzy Systems and Knowledge Discovery, pages 324–328, 2005.

[23] Jie Yang, Weier Lu, and Alex Waibel. Skin-color modeling and adaptation. In ACCV, pages 687–694, 1997.

[24] Jinfeng Yang, Zhouyu Fu, Tieniu Tan, and Weiming Hu. Skin color detection using multiple cues. In Proceedings of the 17th International Conference on Pattern Recognition, pages 632–635, 2004.

[25] Huicheng Zheng, Mohamed Daoudi, and Bruno Jedynak. Adult image detection using statistical model and neural network. Electronic Letters on Computer Vision and Image Analysis, 4(2):1–14, 2003.

[26] Huicheng Zheng, Mohamed Daoudi, and Bruno Jedynak. Blocking adult images based on statistical skin detection. ELCVIA, 4(2):1–14, 2004.