ILLUMINATION CORRECTION FOR STATIC SKIN FILTERS

Rehanullah Khan [1], *Allan Hanbury* [2], *Amjad Khattak* [3], *Farman Ali Khan* [4], *Imran Maqsood* [5]

[1] Sarhad University of Science and Information Technology, Peshawar, Pakistan
[2] Institute of Software Technology and Interactive Systems, TU-Wien, Vienna, Austria
[3] University of Engineering & Technology Peshawar, Pakistan
[4] COMSATS Institute of Information Technology, Pakistan
[5] University of Engineering & Technology Mardan, Pakistan

ABSTRACT

Illumination correction or Color Constancy (CC) is the ability of humans for resolving the apparent colors of objects in a given scene independently of the illumination source. For robust skin detection in images/videos, we evaluate and investigate the effect of CC approaches on static skin segmentation approaches. The effect of five CC approaches namely Gray-Edge CC, Gray-World CC, max-RGB CC, Shades-of-Gray CC and Bayesian CC is studied for the YCbCr static skin filter. Results on two datasets (DS1 and DS2) having annotated per frame ground truth show that skin classification performance is improved. At the same time, the sift and deviation of the skin locus in the chromaticity space will result in alternating performance.

Keywords: Color constancy, skin detection, static skin detection

1. INTRODUCTION

Many face recognition, detection and gesture tracking systems use skin detection in the early stages of the concerned algorithms [9][4]. Skin information contributes much to object recognition [13]. One of the usage of skin color based tracking, locating and categorization could be blocking unwanted image and video content [5].

Though human skin color can be viewed as a data cluster in a proportionate region of the given color space, the skin color of the same individual differs under alternating lighting conditions. Even under constant illuminant situations, background, shadow and reflections effect the skin-color coverage space. Furthermore, in a moving scenario, the perceived skin color changes as the individual location with reference to the camera and or light varies. This effect is more pronounced in video sequences where the skin color in the consecutive frames slightly differs from the previous frames due to lighting effects, reflections and camera position. Human vision can adapt to the changing lighting conditions. This ability of human being to perceive a constant visual representation of the color of objects is known as CC. For skin detection, the advantage of static filters is the simple and general skin segmentation rules. This results in the construction of skin detection rules which are computationally favorable [11]. For the static filters, one needs to search both a good color space and the optimal decision rules experimentally. Generally, the true positive rate can be increased by tuning but at the same time the false positive rate is also affected [2, 3, 6].

In this paper, for robust skin detection, we evaluate and investigate the impact of CC on static skin detection algorithms. Such an evaluation and investigation is important for detection scenarios, especially, color based skin detection. For CC, we select state-of-the-art CC algorithms. These includes Gray-Edge CC, Gray-World CC, max-RGB CC, Shades-of-Gray CC and Bayesian CC. From the skin detection algorithms set, we select the YCbCr static skin filter from [1] because of its over-all good performance. Results on two datasets (DS1 and DS2) with annotated per frame pixel-level ground truth reveals that since with the CC algorithms, we obtain a compact representation of the skin locus, skin classification performance is improved. At the same time, any shift and deviational skin locus in color coordinates result in alternating performance.

The rest of the paper is organized as follows: Section 2 explains the static skin filter. Section 3 discusses color constancy in general. Section 4 discusses the datasets used and the evaluation setup, whereas, Section 5 concludes this paper.

2. STATIC HUMAN SKIN FILTER

Human skin color can be approximated in a well defined cluster given a color space, if the recording conditions in the images remain consistent (illumination controlled environment)[12]. Based on this idea, one approach is constructing a static human skin filter or in other words the static skin classifier. A static skin approach tackles the problem by defining explicit skin detection rules based on the boundaries of the skin cluster in a given color coordinate system. Different ranges of static values for each color space channel (for example, R of RGB color space) are constructed and the given pixel values falling within the pre-defined value ranges are flagged as skin data. The main benefit of this approach is simple skin segmentation rules and the computational efficiency because it is pixel based. However, the major drawback is finding both an optimal color model and the perfect skin discrimination rules [11]. 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.

We use the static skin filter of [1] in the YCbCr color space. Chai and Ngan [1] take advantage of the distribution of human skin chrominance in color images. A static skin filter is derived from the chrominance data of the color skin images. and therefore, skin color can be represented by the static values of Cb and Cr component of the YCbCr color space [1]. 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 [1],

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

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

3. ILLUMINATION CORRECTION

CC relates to the ability of an individual for resolving the perceived colors in a scene irrespective of the illumination source used [4]. More formally, assuming that an image I is composed of [10]:

$$I(X) = \int_W E(\lambda)C(\lambda)S(X, \lambda)D\lambda \tag{2}$$

where $E(\lambda)$ is the chrominance spectrum of the incident lighting source, $S(X, \lambda)$ is the reflectance parameter of the surface and $C(\lambda)$ is the sensor function related to its sensitivity. The terms W and X covers the visible chrominance lighting spectrum and the geometrical spatial coordinates respectively [10]. The goal of CC is to estimate the unknown term $E(\lambda)$:

$$e = \int_W E(\lambda)C(\lambda)D\lambda \tag{3}$$

Different CC algorithms provide different estimation of the illuminant E. In the following, we evaluate Gray-edge hypothesis CC, Gray-world hypothesis CC, max-RGB CC, Shades-of-gray CC and Bayesian CC for static skin detection approach.

4. EVALUATION

In an experimental setup, the objective is an investigation and an evaluation of the role model of CC algorithms for the skin detection algorithms. For this purpose, we opt for the two datasets DS1 and DS2. DS1 is used in [7] and the DS2 is created by Sigal et. al. [8]. In the following, the two datasets DS1 and DS2 are discussed followed by an experimental evaluation.

For the dataset DS1, 15 videos are suggested by an Austrian service provider. Confusing backgrounds are selected for providing variation, thus adding an extra challenge (see Figure 1). 10 more videos are added for further challenging situations such as large variation in skin-colors, for example, the different skin-colors in the corresponding frames. The dataset also contains scenarios having many people with visible body parts, both indoors and outdoors, with different cameras and the lighting also varies from normal daylight to directional stage lighting [6]. Sequences contain shadows and minor occlusions as well and vary from 100 frames to 500 frames and have data errors with generally poor quality [6]. For all the video sequences, ground truth is available. However, for experiments, only the *skin-only* set from this dataset is used. The annotated videos are available on-line[1].

The dataset DS2 is used in [8] containing 21 high quality videos from popular movies. It covers variety of people from different ethnicities, recording conditions and skin colors. Multiple people with multiple visible body parts are also considered. The video sequences are shot indoors and outdoors, using static and moving cameras. They vary in length from 100 images per video to 300 images and are high quality compared to DS1. Figure 2 depicts example images from the dataset DS2. The sequences are hand-labeled and ground truth is available for every image of every video.

Fig. 2. Example frames from dataset (DS2) consisting of 21 video sequences. (Source: [8]).

In the evaluation, we show the impact of Gray-Edge CC, Gray-World CC, max-RGB CC, Shades-of-Gray CC and Bayesian CC on the static skin filter. For skin filter, we select the static filter in YCbCr color space because of its transformation simplicity, explicit separation of luminance and chrominance and its wide usage for skin detection [11]. F-measure is used as an evaluation measure. Figure 3 shows the

[1] `http://www.feeval.org/`

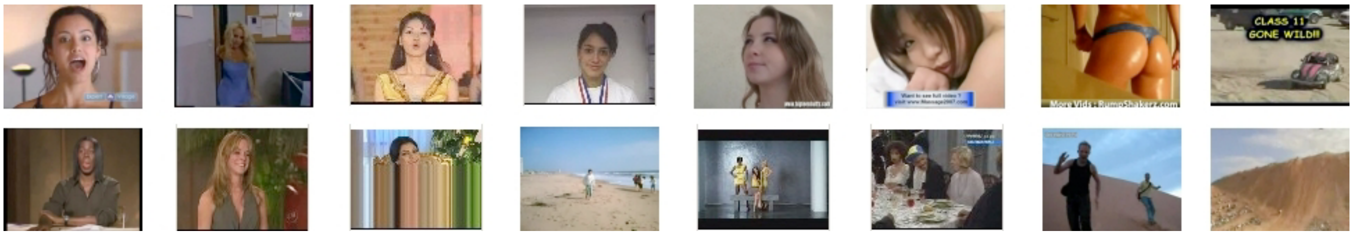
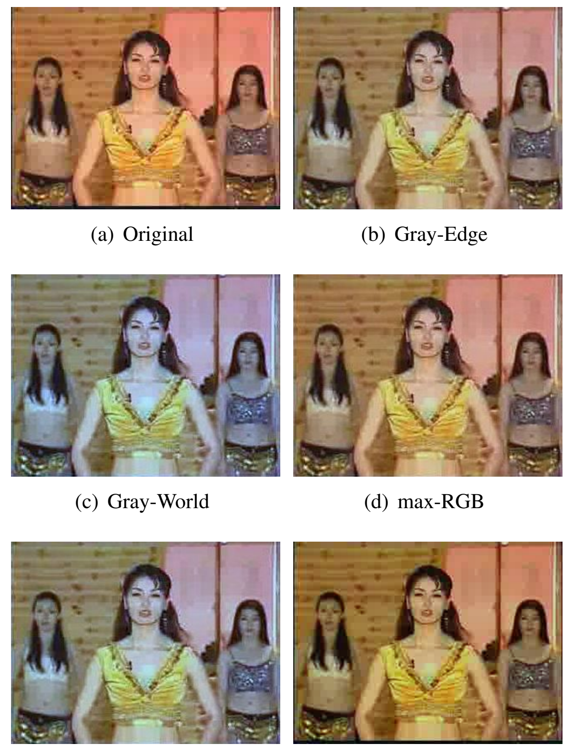


Fig. 1. Example frames from the annotated video dataset (DS1). Source [6]



(a) Original (b) Gray-Edge
(c) Gray-World (d) max-RGB
(e) Shades-of-Gray (f) Bayesian

Fig. 3. The outputs of different CC algorithms. (a) Original frame. (b)-(f): Results of applying the indicated algorithm.

output of the CC algorithms used. Figure 4 shows two examples of the result of skin detection after applying Gray-World CC. Figure 4(a)(d) shows original images, Figure 4(b)(e) shows skin detection using the static filter in the YCbCr color space and Figure 4(c)(f) shows improved skin detection using the same filter after applying the Gray-World algorithm. This result clearly shows the benefit of using lighting correction for skin detection. Color constancy can however negatively affect the results. As shown in Figure 5(c), the application of lighting correction has resulted in reporting pixels that do not belong to skin as skin pixels and thus increasing false positives. Figure 5(f) reports a scenario where the application of a lighting correction algorithm decreased true positives.

Figure 6 shows F-measure for DS1 (*skin-only* set) and DS2. We select DS1 skin-only set because we are interested, specifically in the effect of CC algorithms on skin pixels only. For DS1, we find that the F-measure of 0.58 without using lighting correction is decreased to 0.55 by using the Gray-Edge algorithm. Gray-World also reports decreased performance with an F-measure of 0.46 while in the case of max-RGB, the skin detection performance is increased to 0.60. Shades-of-Gray reports decreased performance of 0.53 and Bayesian reports a slight increase with F-measure of 0.59 over the original uncorrected result.

For dataset DS2 (Figure 6), by applying lighting correction, the results are improved in all the cases. We find that the F-measure is slightly increased by using the Gray-Edge algorithm and max-RGB. Gray-World reports an increased performance with F-measure of 0.41. Shades-of-Gray reports an increased F-measure of 0.40 and Bayesian CC shows an incremented F-measure of 0.35 over the original uncorrected result.

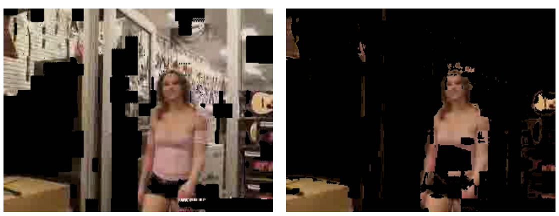
From the results, it is observed that the usage of CC algorithms prior to using static skin filters can improve skin detection performance (DS2 results). However, the CC algorithms can mislead the performance (when using F-measure, for example, the DS1 results). This is because that CC algorithms not only compacts the skin locus chrominance space, but also shifts and deviates the skin coverage in a given color space coordinate system. Since the static filters use static boundaries, we therefore, get different results by applying CC algorithms.

5. CONCLUSION

In this paper, we have analyzed the effect of CC algorithms on skin segmentation algorithms and it is observed that the usage of CC algorithms before applying static skin classifiers and filters can improve performance. It is also observed that the CC algorithms achieve a compact skin locus. On the other hand, the CC algorithms also have a negative effect on the segmentation performance. The CC algorithms can not only shift the skin chrominance coverage but also deviate it in the chrominance space. Since the static classifiers and filters use static range values, we therefore, get varying performance by

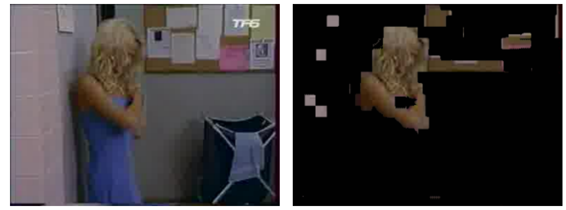
(a) Original frame from a video. (b) Skin detection without CC.

(c) Skin detection after lighting correction. (d) Original frame from a video.



(e) Skin detection without CC. (f) Skin detection after lighting correction.

Fig. 4. Skin detection can be improved by first applying lighting correction using CC algorithms. For skin detection, a static filter in the YCbCr color space is used.



(a) Original frame from a video. (b) Skin detection without CC.

(c) Skin detection after applying the Gray-World algorithm. (d) Original frame from a video.

(e) Skin detection without CC. (f) Skin detection after applying the Gray-World algorithm.

Fig. 5. Color constancy can decrease skin detection performance in some cases. For skin detection, a static filter in the YCbCr color space is used.

applying CC algorithms.

6. 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] 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.

[3] 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.

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

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

[6] 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.

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

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

[9] 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.

[10] J. van de Weijer, T. Gevers, and A. Gijsenij. Edge-based color constancy. *IEEE Transactions on Image Processing*, 16(9):2207–2214, 2007.

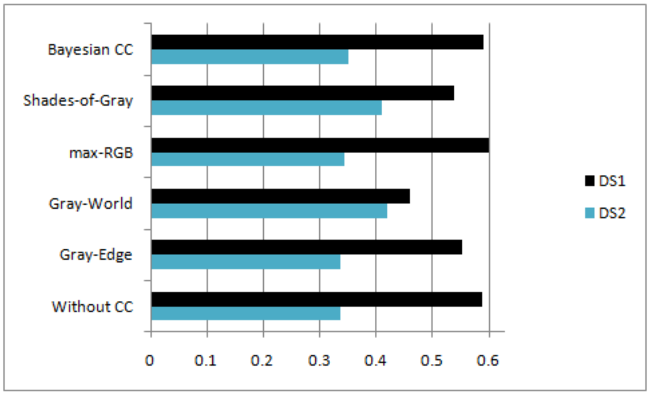


Fig. 6. F-measure: Static filter of YCbCr with CC on DS1 (*skin-only*) and DS2 (complete).

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

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

[13] 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.