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Efficient Human Skin Detection Using 2D Histogram and Gaussian Approach

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Abstract. The efficient human skin detection method is more suitable for many human skin colors with different illumination conditions which is used to skin segmentation. There are many human skin –color detection methods were available but they were not performing efficient with different ethnic. These are algorithm is based on skin colour detection. One of the problems this and similar algorithms have to deal with is sensitivity to the illumination conditions under which the input image is captured. Hence illumination sensitivity influences face detection results. In this paper, we propose a human skin detection approach that combines a smoothed 2-D histogram and Gaussian model, for automatic human skin detection in color image(s). The proposed approach reduces computational costs and it improves the accuracy of skin detection despite wide variation in ethnicity and illumination.

Keywords: 2D Histogram, Gaussian model, skin detection

1. Introduction

The progress of information society today, images have become more and more important. Among them, skin detection plays an important role in a wide range of image processing applications from face tracking, gesture analysis, content-based image retrieval systems to various human–com-puter interaction domains [1]–[6]. In these applications, the search space for objects of interests, such as hands, can be re-duced through the detection of skin regions. One of the simplest and commonly used human skin detection methods is to define a fixed decision boundary for different color space components [7]–[9]. Single or multiple ranges of threshold values for each color space components are defined and the image pixel values that fall within these predefined range(s) are selected as skin pixels. In this approach, for any given color space, skin color occupies a part of such a space, which might be a compact or large region in the space. Other approaches are multilayer per-ceptron [*9]-[10*], Bayesian classifiers [7]–[9], and random forest [10]. These aforementioned solutions that use single fea-tures, although, successfully applied to human skin detection; they still suffer from the following. 1) *Low Accuracy:* False skin detection is a common problem when there is a wide variety of skin colors across different ethnicity, complex backgrounds and high illumination in image(s). 2) *Luminance-invariant space:* Some robustness may be achieved via the use of luminance invariant color space [1,3]; however, such an approach can withstand only changes that skin-color distribution undergo within a narrow set of conditions and also degrades the per-formance [9]. 3) *Require large training sample:* In order to define threshold value(s) for detecting human skin, most of the state-of-the-art work requires a training stage. One must under-stand that there are tradeoffs between the size of the training set and classifier performance. First of all, we employ an online dynamic approach as in [7] to calculate the skin threshold value(s). Therefore, our proposed method does not require any training stage beforehand. Second, a 2-D histogram with smoothed densities and a Gaussian model are used to model the skin and nonskin distributions, respectively. Finally, a fusion strategy framework using the product of two features is employed to perform automatic skin detection. To the best of our knowledge, this is the first attempt that employs a fusion strategy to detect skin in color image(s). The image pixels representation in a suitable color space is the primary step in skin segmentation in color images. A better survey of different color spaces (e.g., RGB, YCbCr, HSV, CIE Lab, CIE Luv, and normalized RGB) for skin-color representation and skin-pixel segmentation methods is given by Sobottka *et al.* [8].

2. Related Work

Skin detection is the process of finding skin-color pixels and regions in an image or video. In images and videos, skin color is an indication of the existence of humans in media. In one of the early applications, detecting skin-color regions was used to identify nude pictures on the Internet for content filtering.

A skin classifier defines a decision boundary of the skin-color class in the color space based on a training database of skin-color pixels. For example, the fixed range values on the HS color space where the pixel values belong to skin pixels in the range of R_H=[0,50] and R_S=[0.23,0.68] threshold values in RG space and HSV space where threshold values are set to be within the range R_r = [0.36,0.465], R_g= [0.28,0.363], R_H=[0,50], R_S=[0.20,0.68] and R_V=[0.35,1.0]to differentiate skin and non skin pixels. In these approaches, high false skin detection is a common problem when there are a wide variety of skin colors across different ethnicity, complex backgrounds, and high illumination. Some robustness may be achieved via the use of luminance invariant color spaces [1], [9]; however, such an approach can only cope if the change in skin-color distribution is within a narrow set of conditions [8]. Other approaches are multilayer perceptron [9,10], Bayesian classifiers [7–9], and random forest [6]. In multilayer perceptron-based skin classification, a neural network is trained to learn the complex class conditional distributions of the skin and nonskin pixels the proposed a Kohonen network-based skin detector where two Kohonen networks, skin only and skin plus nonskin detectors, were trained from a set of about 500 manually labeled images to obtain an optimal result. Sebe*etal.* [6] used a Bayesian network with training data of 60 000sam-ples for skin modeling and classification. Hancke et al. [7] proposed the use of tree-augmented Naive Bayes classifiers for skin detection. our proposed method has two advantages in comparison to the state-of-the-art solutions. First of all, our proposed skin detection method employs an online dynamic threshold approach. With this, a training stage can be eliminated. Second, we select a fusion strategy for our skin detector. Human skin detection method that is adaptable to different human skin colors and illumination conditions is essential for better human skin segmentation. To the best of our knowledge, this is the first attempt that employs a fusion strategy to detect skin in color image(s).

3. Our Method

Fig. 1 shows the proposed framework for automatic skin detection. First, an approach is adopted to obtain the face(s) in a given image. Second, a dynamic method is employed to calculate the skin threshold value(s) on the detected face(s) region. Third, two features—the 2-D histogram with smoothed densities and Gaussian model—are introduced to represent the skin and non skin distributions, respectively. In this paper, the RGB color space is converted to the LO space [4] to mimic visual human perception [8].

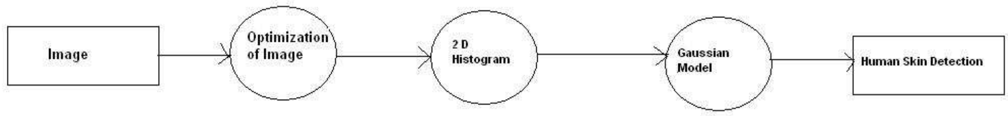

Figure 1: Data flow diagram

- The input image of size 250x 250
- The input image is resized the size of 125x 125
- The RGB image is converted to gray scale image in order to reduce the noise
- The skin region is detected from the Gaussian model

3.1. Preprocessing

In the preprocessing steps, for any given image(s), S_t where t is the number of images, t € {1, 2 ….T} we first locate human eyes. Then, an elliptical mask model as illustrated in Fig. 3 is used to generate the elliptical face region. in the image(s). Here,(x_0,y_0) is the center of the ellipse as well as the eyes symmetry point. Minor and major axes of the ellipse are represented by1.6D and 1.8D, respectively, where D is the distance between two eyes. Then, the detected edge pixels are further dilated using a dilation operation to get the optimal nonsmooth regions. Finally, we obtain a new image(s),S'_t that only consist(s) of face regions.

3.2. Color Space

An image can be represented in a number of different color space models (ie. RGB,HSV[1],YC_rC_t). These are some color space models available in image processing. Therefore, it is important to choose the appropriate color space for modeling human skin color. In this paper, we propose the use of the LO color space [4]; the reason is twofold: first, color opponency is perceptually relevant as it has been proved that the human visual system uses an opponent color encoding [9,10]; and second, in this color space, the use of logarithms renders illumination change to a simple translation of coordinates. Even though different human skin-color detection solutions have been successfully applied, they are prone to false skin detection and are not able to cope with the variety of human skin colors across different ethnic. Moreover, existing methods require high computational cost. The proposed approach reduces computational costs as no training is required, and it improves the accuracy of skin detection despite wide variation in ethnicity and illumination.

LO Space: The theory of opponent colors was first studied by C. S. Chan, [4] in 1892. He observed that certain colors are never perceived together in the human visual system. For instance, we never see yellowish-blue or reddish-green. Based on this theory, the LO is a representation of color information by applying logarithms to the opponency model so that it is simple to model illumination changes. As illumination changes, log component chromaticity distributions undergo a simple translation. These distributions are coded by using means and first -moments found using principle component analysis [6].

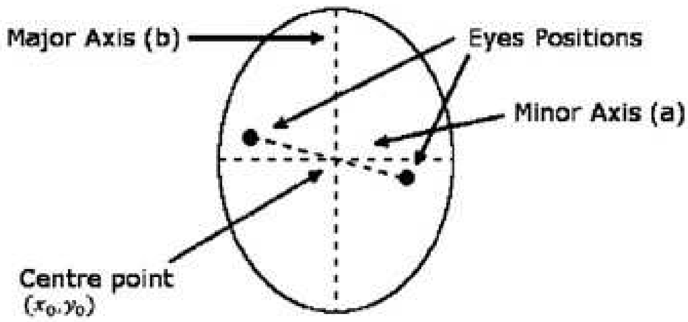

Figure 2: Elliptical mask model generated using eye coordinates

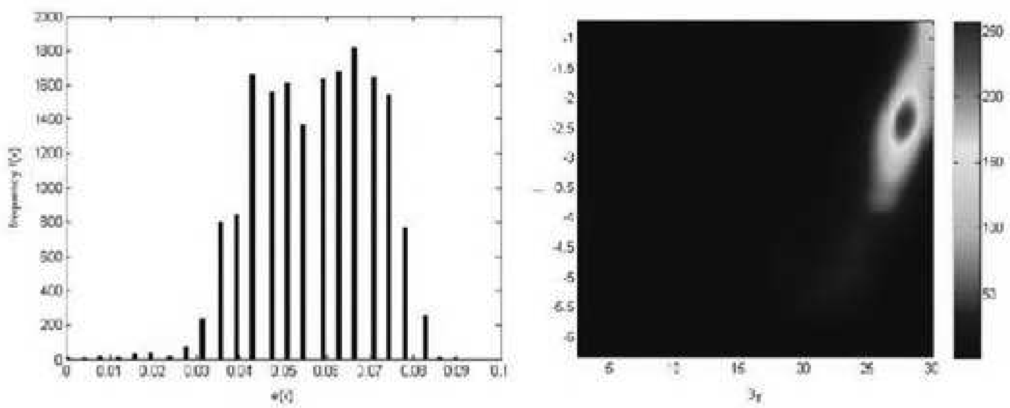

Figure 3: (a) and (b) Histograms of 1-D and 2-D:
(a) As only one channel with frequency at y axis and
(b) Two different channels of the same color space on x axis and y axis.

3.3. Skin Detection

1) Dynamic Threshold with Smoothed 2-D Histogram: Human skin color varies greatly between different ethnicity [1]. Nonetheless, skin appearance in color image(s) can also be affected by illumination, background image, camera characteristic, etc. In our approach, we employ an online dynamic approach as to [9] to calculate the skin threshold value(s) on the face images, S_t . The assumption is that the face and body of a person always share the same colors. However, instead of using the 1-D histogram, as illustrated in Fig. 3(a), we introduce a 2-D histogram [see Fig. 3(b)] with smoothing densities [3]. In this paper, the feature vector for the smoothed 2-D histogram, Z is represented by the combination of I and B_y. The smoothed 2-D histogram-based skin segmentation, D_{hist}, at pixel n is given as

$$D_{hist}(S_t,Z) = \begin{cases} 1 \; if Z(In, Byn) > 20 \\ 0 \; if \; Z\,(In, Byn) \leq 20 \end{cases}$$

$$I_n,\, B_{yn}, \in S_t \qquad (1)$$

2) Gaussian Model: The Gaussian model is a sophisticated model that is capable of describing complex-shaped distributions and is popular for modeling skin-color distributions. The threshold skin-color distribution in the 2-D histogram is modeled through elliptical Gaussian joint probability distribution functions defined as

$$\rho(H|\,\lambda) = \sum_{i=1}^{k} w_i g\,(c|\mu_{i,\,\sum i}) \qquad (2)$$

where H is the color vector of (I,By),λ ={$w_i\mu_{i,\ \sum i}$ }μ_i is the mean vector, and $^{\sum i}$ is the diagonal covariance matrix, respectively. w_i refers to the mixing weights, which satisfy the constraint $\sum_{i=1}^{k} \pi i = 1$. The result of Gaussian model-based skin detection, D_{gmm}, can be obtained by using Fig 3(b). μ is the center of the Gaussian model, while τ is the angle between x axis and the line D. Let (I_i ,By_i) be the coordinate of pixel n and is positioned on the red dot along lineD. Distance of (I_n ,B_{yn}), d and angle τ are calculated as follows:

$$d = \sqrt{dx^2 + dy^2} \qquad (3)$$

$$\tau = \tan^{-1}\frac{dy}{dx} \qquad (4)$$

where dx and dy are the distance between (I_n,B_{yn}) and centre, μ at x axis and y axis respectively. μ_x and $\mu_y$are the coordinate of μ at x axis and y axis respectively. Distance between the boundary and centre of the Gaussian model at x axis and y axis, D_x axis and D_y axis at given angle, τ are as follows:

$$D_x = \textstyle\sum_x \cos(\tau) \qquad (5)$$

$$D_y = \textstyle\sum_y \sin(\tau) \qquad (6)$$

where $\sum_x$ and $\sum_y$ are the variance of x axis and y axis for gaussian model. Distance D is represented as

$$D = \sqrt{Dy^2 + Dx^2} \qquad (7)$$

Therefore, D_{gmm} is given as

$$D_{gmm}(S_t,\mu,\textstyle\sum) = \begin{cases} 1 \,, if \; D > d \\ \quad 0. \end{cases} \qquad (8)$$

The combined matching results using the fusion rules can be obtained as follows:

$$D(S_t) = \Gamma\{Dhist(St, Z)|Dgmm(St, \mu, \textstyle\sum)\} \qquad (9)$$

where Γ is the selected rule, which represents the product. In order to make the fusion issue tractable, the individual features are assumed to be independent of each other.

4.3. Fusion Strategy

In order to increase the effectiveness and robustness of the skin detection algorithm, a fusion strategy is proposed by inte-grating the two incoming single features into a combined single representation. Both models will vote for classification of skin and nonskin pixels. This can be done by using product rule to both models. matching results produced by the smoothed 2-D histogram of popular public video clips from web platforms. These are chosen from the community (top-rated) and cover a large variety of different skin colors, illuminations, image quality, and difficulty levels.

4. Experiments

In this section, the performance of the proposed approach under different conditions, such as fusion strategy, color spaces, and a comparison with the state-of-the-art methods in terms of qualitative and quantitative performance. We only perform quantitative analysis on the dataset [4] as ground truth videos are only available for this dataset.

Experiments are conducted using three public databases. Pratheepan's dataset [9]. It consists of a set of images downloaded randomly from Google. These random images are captured with a range of different cameras using different color enhancements and under different illuminations.

4.1. Results and Analysis

The detection results for each dataset are to be added, respectively. When there is no face detected on our proposed method does not require any training stage beforehand. Second, a 2-D histogram with smoothed densities and a Gaussian model are used to model the skin and nonskin distributions, respectively. Finally, a fusion strategy framework using the product of two features is employed to perform automatic skin detection. To the best of our knowledge, this is the first attempt that employs a fusion strategy to detect skin in color image(s). The image pixels representation in a suitable color space is the primary step in skin segmentation in color images. A better survey of different color spaces (e.g., RGB, YCbCr, HSV, CIE Lab, CIE Luv, and normalized RGB) for skin-color representation and skin-pixel segmentation methods is given by Kakumanue. [8].

Finally, the proposed approach does not require any training stage and, hence, is more effective in terms of computational cost as opposed to approaches. In our experiments, we noticed that the final result of our work depends greatly on the outcome of the preprocessing phase. If the algorithm detects a false face region, poor result will be returned. The result of skin segmentation for false face region detected. When a false face region is obtained, false dynamic thresholds will be generated. Therefore, false classifications will be processed, where non skin regions are classified as skin regions. we will investigate the face detector algorithm to overcome this problem. In this research work we have made a humble attempt to propose an algorithm for human skin detection in colour images in the presence of varying lighting conditions, for varied skin colours as well as with complex backgrounds. Based on a novel tangible skin component extraction modus operandi and detection, our method detects skin regions over the entire image and engenders human skin detection based on the signatures of the detected skin patches. The algorithm constructs the boundary for each skin detection using Gaussian model. Experimental results demonstrate successful skin detection over a wide range of facial variations in colour, position, scale, varying lighting conditions, orientation, 3D pose, and expression in images from the database. The modified image is subjected to skin detection algorithm which detects only the true skin regions in the image. The complexity involved in computation is relatively more proficient when compared to that of the prior developed methodologies because of the fact that the luminance information is excluded from the computation our algorithm can detect multiple human skin with a wide range of facial variations in an image. It works works efficiently for occluded faces, faces of any size, faces with glasses, intensity variations etc.

(a) (b) (c)

Figure 4: (a) Input image, (b) existing method, (c) our proposed method

Colour space	Accuracy	F-score	True Positive Rate	False Negative Rate
IB_y	**0.9039**	**0.6490**	**0.6580**	**0.3420**
HS	0.9057	0.6512	0.6521	0.3479
HV	0.7977	0.4549	0.6521	0.3479
SV	0.8898	0.6285	0.6905	0.3995
YC_b	0.8936	0.6143	0.6277	0.3723
YC_r	0.8985	0.6392	0.6656	0.3344
C_bC_r	0.9151	0.6241	0.5223	0.4777

Table 1: multiple features (the fusion of 2D histogram and GMM).

4.2. Comparison between Different Color Spaces

In this section, we analyze seven different combinations of feature vectors:

The results for each feature vector are presented true positive rate and lower false negative rate than HS. Also, it has been proven that the human visual system uses an opponent color coding.

4.3. Fusion Strategy Results

In this section, we show the comparison result of using single feature—smoothed 2-D histograms (s2D) or Gaussian mixture models (GMM) only, and multiple features (the fusion of s2D and GMM). The results are illustrated in Fig.4 and Table I. Fusion Approach has the highest accuracy and F-score. More-over, it can also be visualized that the fusion strategy has lower false positive rate compared to the single feature approach. For instance, the smoothed 2-D histogram is able to detect most of the skin regions, but it is highly occluded with noise.

5. Conclusion

In this paper, the efficient skin detection based on smoothed 2-D histogram and Gaussian model has been proposed to automatic detect human skin in image(s). As exhibited in experiments, the proposed method outperforms state-of-the-art methods in terms of accuracy in different conditions: background model, illumination, and ethnicity. With this, it shows the potential to be ap-plied to a range of applications such as gesture analysis. One drawback of the proposed approach is that its success relies on eye detector algorithms. However, this is the general problem faced by all other researchers who work in this domain. Our future work is focused on building a better preprocessing method, to use field-programmable gate arrays to implement a hardware scheme.

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