Dynamic clustering for skin detection in YCbCr colour space

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Abstract: *This paper presents a new approach for skin detection in colour images. The method is based on the building of a dynamic clustering in the YCbCr colour space, taking into account the illumination conditions of the examined image. The results of a comparative evaluation on a publicly available database, show that the proposed method outperforms well known rule based static methods, both in qualitative and quantitative terms.*

Keywords**:** skin detection, dynamic clustering, YCbCr colour space

1. INTRODUCTION

Skin detection in colour images is an important topic in many kinds of applications: face detection and recognition [1], hand gestures detection and tracking [2-3], nude images and video blocking [4-5]. Skin detection is used to identify the pixels of an image that are related to human skin. A useful feature to detect skin pixels is the colour that results to be a valid information, robust against rotations, scaling and partial occlusions. Moreover, skin-colour based methods do not require a long processing time, differently from other methods that require the processing of other image features [6].

Generally, a skin-colour based method works by transforming the colour image in an appropriate colour space, where is simpler to separate skin from non-skin pixels. Usually, this separation is accomplished using a distance metric between a pixel colour and the predefined skin colour model. However, the use of the colour information is a challenging task, because the appearance of skin pixels is affected by various factors: illumination conditions that can produce many false negatives; the presence in the background of skin-like coloured objects, which can produce many false positives. In some cases, skin colour can also be used as a complementary information to other features such as shape and texture, to build more accurate skin detection methods [7-8], but reducing the computational efficiency.

The colour skin detection methods can be grouped into three types: parametric, nonparametric and explicit skin cluster definition methods. Parametric and nonparametric methods could be complex and computational inefficient for use in real-time applications.

In the present work, an explicit skin cluster method, which works in the YCbCr colour space, is presented. The proposed method tries to minimize both false positives and false negatives, taking into account the illumination conditions of the image and it results to be computationally efficient for real-time applications.

The rest of the paper is organized as follows: Section 2 covers related work in skin detection; in Section 3, the proposed approach is presented; in Section 4, some results and comparison carried out on a publicly available database are reported; finally, Section 5 concludes the paper.

2. RELATED WORK

Many surveys on skin detection have been presented in recent years [9-11]. Human skin colour has been modelled in many colour spaces. The choice of the colour space can be considered as the primary step in the design of a skin colour detector [13]. The definition of an optimal colour space for skin detection was addressed in [12]; the authors conclude that in every colour space it is possible to define appropriate skin detection rules.

The *RGB* colour space is the default colour space for most available image formats. In [14] a rule based method in *RGB* colour space is presented for skin colour detection. Starting from *RGB*, linear or non-linear transformations can be used to obtain a new colour space. The colour space transformation can be useful to decrease the overlap between skin and non-skin pixels, above all in the case of different illumination conditions.

Usually, it is a common practice to ignore the luminance component in the skin detection process, since it does not result to be discriminant [15-16]. Two particular colour spaces that separate the luminance and the chrominance components are *HSV* and *YCbCr*, which indeed are the most commonly used in skin colour detection approaches. The *HSV* colour space is built through a non-linear transformation from the *RGB* space, where Hue (*H*) and Saturation (*S*) are the chrominance components, while Value (*V*) is the luminance components. Most of the methods that work in this colour space ignore the luminance component [15,17]; however, also methods that include the luminance in the process of skin detection have been presented [18].

The *YCbCr* colour space is built from a linear transformation from the *RGB* colour space: the chrominance components *Cb* and *Cr* are obtained by subtracting the luminance component *Y* from blue and from red, respectively. Also in this case, some methods ignore the luminance components [16], whereas other take it into account [19]. However, it has been demonstrated that the luminance component should be included in the process of skin detection, because the skin colour is non-linearly dependent on the luminance component in different colour spaces [19,20].

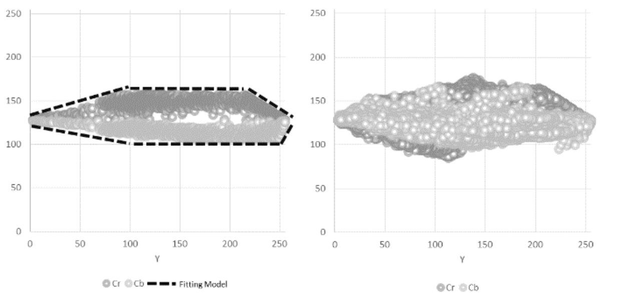
Independently from the choice of the colour space, many algorithms have been proposed for skin colour pixel classification, in order to obtain the skin pixel detection. They include linear classifiers [14-20], Bayesian [21,22] or Gaussian classifiers [20,23], and artificial neural network [24-25]. Most commonly, the explicit rules, used to separate skin and non-skin pixels in a colour space, are based on the shape of the distribution of skin pixels (e.g., rectangle and ellipse) or can have more complex forms.

In particular, in [19], the authors introduce two different skin cluster models that take into account the luminance component. According to the first model, the skin clusters are determined by two central curves and by their spreads in the *YCbCr* space. In the second model, the skin cluster is represented by an ellipse in a transformed *CbCr* subspace. A large set of fixed parameters have been computed by training samples of skin patches to construct the two skin colour models.

In this work, we present a novel method that works in the *YCbCr* colour space. It takes into account the luminance component, but differently from other methods [14-16], we dynamically calculate the range of *Cb* and *Cr*, by taking into account the illumination conditions of the current image.

3. THE PROPOSED APPROACH

As already shown in [19], *YCb* and *YCr* subspaces for skin tone exhibit a trapezoidal shape in pixel distribution (see figure 1.a), differently from distribution of skin and non-skin pixels (see figure 1.b).



(a) (b)

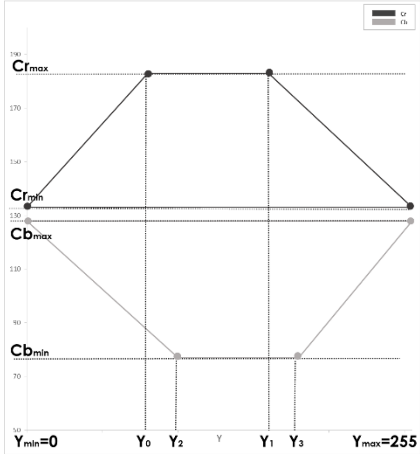
Fig. 1: *Cr* and *Cb* components as function of *Y* component for a given image: (a) skin pixel distribution; (b) skin and non-skin pixel distribution

Moreover, we experimentally observed that size and shape of these trapezia change depending on the illumination conditions. In particular, we have observed that:

a) the bases of the trapezia representing the skin colour clusters for images in high illumination conditions are larger than those associated with the skin colour clusters in low illumination conditions;
b) the vertices of the trapezia change their positions in dependence on the luminosity of the image;
c) the maximum of *Cr* and the minimum of *Cb* strongly change with the illumination conditions, whereas the minimum of *Cr* (in the following Cr_{min}) and the maximum of *Cb* (in the following Cb_{max}) are almost fixed at the values 133 and 128, respectively, as reported in [16];
d) the values of the *Cr* and *Cb* components for the skin pixels, generally satisfy the following conditions:

$$133 \leq Cr \leq 183$$
$$77 \leq Cb \leq 128$$

On the basis of these observations, the proposed method defines a dynamic fitting model of the skin colour



clusters of the *YCb* and *YCr* subspaces.

Fig. 2: Graphical representation of Y_{min}, Y_{max}, Y_0, Y_1, Y_2, Y_3, Cr_{max}, Cr_{min}, Cb_{max}, Cb_{min}.

For the sake of simplicity, we will refer to the figure 2 to explain the proposed procedure to build the skin colour clusters. The vertices of the larger basis of the trapezium associated with the *YCr* skin subspace are given by (Y_{min}, Cr_{min}) and (Y_{max}, Cr_{min}), where Y_{min}=0, Y_{max} =255 and Cr_{min} = 133. Similarly, the vertices of the larger basis of the trapezium associated with the *YCb* skin subspace are given by (Y_{min}, Cb_{max}) and (Y_{max}, Cb_{max}), with Cb_{max} = 128.

The coordinates of the vertices of the shorter basis of the trapezium associated with the *YCr* skin subspace are set to (Y_0, Cr_{max}) and (Y_1, Cr_{max}). Cr_{max} is computed by taking into account the histogram of the pixels with values of *Cr* in the range [133, 183], looking for the maximum of *Cr* that is associated with at least a 10% of image pixels. Y_0 and Y_1 values are set as the 5[th] percentile and the 95[th] percentile of the *Y* component, respectively, considering all the pixels of the image with $Cr = Cr_{max}$.

The same procedure is used to find the coordinates (Y_2, Cb_{min}) and (Y_3, Cb_{min}) of the vertices of the shorter basis of the trapezium associated with the *YCb* skin subspace. For each *Y* value, a point on the upper border of the trapezium in the *YCr* subspace has coordinates (*Y*, $K_{Cr}(Y)$), while a point on the lower bound of the trapezium in the *YCb* subspace, has coordinates (*Y*, $K_{Cb}(Y)$), where $K_{Cr}(Y)$ and $K_{Cb}(Y)$ are given by:

$$K_{Cr}(Y) = \begin{cases} Cr_{min} + d_{Cr}\dfrac{Y - Y_{min}}{Y_o - Y_{min}} & Y \in [Y_{min}, Y_0\,[\\ Cr_{max} & Y \in [Y_0, Y_1\,[\\ Cr_{max} - d_{Cr}\dfrac{Y - Y_1}{Y_{max} - Y_1} & Y \in [Y_1, Y_{max}] \end{cases}$$

where $d_{Cr} = Cr_{max} - Cr_{min}$

$$K_{Cb}(Y) = \begin{cases} Cb_{max} - d_{Cb}\dfrac{Y - Y_{min}}{Y_2 - Y_{min}} & Y \in [Y_{min}, Y_2\,[\\ Cb_{min} & Y \in [Y_2, Y_3\,[\\ Cb_{min} + d_{Cb}\dfrac{Y - Y_3}{Y_{max} - Y_3} & Y \in [Y_3, Y_{max}] \end{cases}$$

where $d_{Cb} = Cb_{max} - Cb_{min}$

(a) (b) (c) (d) (e) (f)

Figure 3: Qualitative analysis of skin detection results on the Compaq database: (a) the input image; (b) the ground truth; (c) Chai, Ngan [16]; (d) Hsu et al. in the YCbCr space [19]; (e) Hsu et al. in the CbCr subspace [19]; and, (f) the proposed method.

Finally, we classify a pixel as skin pixel, if it satisfies the following two conditions:

$$Cr(Y) \in [Cr_{min}, K_{Cr}(Y)]$$

$$AND$$

$$Cb(Y) \in [K_{Cb}(Y), Cb_{max}]$$

4. RESULTS AND COMPARISON

We have compared the proposed method with: the method described in [16], which works in the YCbCr colour space but with a fixed colour cluster; the method proposed in [19], since we started with the same idea that YCb and YCr skin tone subspaces have a trapezoidal shape.

In figure 3, we show some qualitative results of the methods for selected images of the Compaq database [22]. This database consists of 4,675 colour images, which contain skin pixels belonging to persons of different origins and with unconstrained illumination and background conditions.

The qualitative analysis (see figure 3), shows that the method proposed in [16] generally obtains good results, but in some cases, many false negatives are detected (see row 1 and 6); moreover, the pixels belonging to regions of eyes and mouth are generally wrongly detected as skin pixels.

The method [19] detects many false positives, particularly in presence of high or low illumination conditions (see row 3 and 4); its formulation in the CbCr subspace results to improve the skin detection performance, but in some cases it results in the detection of many false negative pixels (see row 1, 4 and 6).

Table 1. Quantitative analysis of the skin detection methods on the Compaq database

Method	F-Measure
CbCr [16]	0.4373
YCbCr [19]	0.3104
CbCr [19]	0.4312
Proposed method	**0.4649**

Then, we report the quantitative results, in terms of F-measure, for all the analysed methods in table 1.

Finally, we evaluated the computational effort of the proposed method, The performance of the algorithm has been evaluated on a PC equipped with an Intel Xeon E5-2623 at 3 GHz, and with 16 GB RAM. For an image with a size of 320x480, the execution time is, on average, 8 ms.

5. CONCLUSION

A novel method for skin detection in colour images has been presented. The approach is based on a dynamic skin pixel clustering in the YCbCr colour space, taking into account the luminance of the currently examined image.

The comparison with other well-known methods in literature shows that the use of the dynamic range allows the skin detector to obtain a better detection of the skin pixels in unconstrained illumination conditions.

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