RGB-H-CbCr Skin Colour Model for Human Face Detection

Nusirwan Anwar bin Abdul Rahman, Kit Chong Wei and John See†
Faculty of Information Technology, Multimedia University
johnsee@mmu.edu.my†

Abstract

While the RGB, HSV and YUV (YCbCr) are standard models used in various colour imaging applications, not all of their information are necessary to classify skin colour. This paper presents a novel skin colour model, RGB-H-CbCr for the detection of human faces. Skin regions are extracted using a set of bounding rules based on the skin colour distribution obtained from a training set. The segmented face regions are further classified using a parallel combination of simple morphological operations. Experimental results on a large photo data set have demonstrated that the proposed model is able to achieve good detection success rates for near-frontal faces of varying orientations, skin colour and background environment. The results are also comparable to that of the AdaBoost face classifier.

Keywords*: Face detection, skin colour, colour models, skin classification, skin modeling.*

1. Introduction

Detection of the human face is an essential step in many computer vision and biometric applications such as automatic face recognition, video surveillance, human computer interaction (HCI) and large-scale face image retrieval systems. The first step in any of these face processing systems is the detection of the presence and subsequently the position of human faces in an image or video.

The main challenge in face detection is to cope with a wide variety of variations in the human face such as face pose and scale, face orientation, facial expression, ethnicity and skin colour. External factors such as occlusion, complex backgrounds, inconsistent illumination conditions and quality of the image may also contribute significantly to the overall problem.

Throughout the last decade, there has been much development in face detection research, particularly in the abundance of methods and approaches. Recent surveys [1], [2] have comprehensively reviewed various face detection methods available in the literature.

Face detection in colour images has also gained much attention in recent years. Colour is known to be a useful cue to extract skin regions, and it is only available in colour images. This allows easy face localisation of potential facial regions without any consideration of its texture and geometrical properties.

Most techniques up to date are pixel-based skin detection methods [3], which classifies each pixel as skin or "non-skin" individually, and independently from its neighbours. Early methods use various statistical colour models such as a single Gaussian model [4], Gaussian mixture density model [5], and histogram-based model [6].

Some colour spaces have their luminance component separated from the chromatic component, and they are known to possess higher discriminality between skin pixels and non-skin pixels over various illumination conditions. Skin colour models that operate only on chrominance subspaces such as the Cb-Cr [7], [8], [9] and H-S [10] have been found to be effective in characterising various human skin colours.

Skin classification can be accomplished by explicitly modelling the skin distribution on certain colour spaces using parametric decision rules. Peer et al. [11] constructed a set of rules to describe skin cluster in RGB space while Garcia and Tziritas [12] used a set of bounding rules to classify skin regions on both YCbCr and HSV spaces.

In this paper, we present a novel skin colour model RGB-H-CbCr for human face detection. This model utilises the additional hue and chrominance information of the image on top of standard RGB properties to improve the discriminality between skin pixels and non-skin pixels. In our approach, skin regions are classified using the RGB boundary rules introduced by Peer et al. [11] and also additional new rules for the H and CbCr subspaces. These rules are constructed based on the skin colour distribution obtained from the training images. The classification of the extracted regions is further refined using a parallel combination of morphological operations. The rest of the paper is organised as follows: Section 2 briefly describes the various steps of our face detection system. The construction of the RGB-H-CbCr skin colour model is described in Section 3. Section 4 presents the use of morphological operations in our algorithm. Experimental results and discussions are provided in Section 5. Finally, Section 6 concludes the paper.

2. System Overview

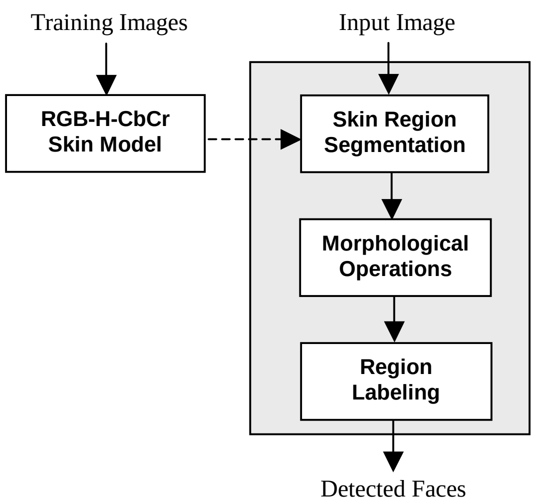


Figure 1. System overview of face detection system

Fig. 1 shows the system overview of the proposed face detection system, which consists of a training stage and detection stage. In our colour-based approach to face detection, prior formulation of the proposed RGB-H-CbCr skin model is done using a set of skin-cropped training images. Three commonly known colour spaces – RGB, HSV and YCbCr are used to construct the proposed hybrid model. Bounding planes or rules for each skin colour subspace are constructed from their respective skin colour distributions.

In the first step of the detection stage, these bounding rules are used to segment the skin regions of input test images. After that, a combination of morphological operations are applied to the extracted skin regions to eliminate possible non-face skin regions. Finally, the last step labels all the face regions in the image and returns them as detected faces. In our system, there is no preprocessing step as it is intended that the input images are thoroughly tested under different image conditions such as illumination variation and quality of image. Since we emphasise on the use of a novel skin colour model in this work, our system is restricted to colour images only.

3. RGB-H-CbCr Model

3.1. Preparation of Training Images

In order to build the skin colour model, a set of training images were used to analyse the properties and distribution of skin colour in various colour subspaces.

The training image set is composed of 140 skin colour patches of ten colour images obtained from the Internet, covering a wide range of variations (different ethnicity and skin colour). These images contained skin colour regions that were either exposed to normal uniform illumination, daylight illumination (outdoors) or flashlight illumination (under dark conditions). The skin regions in all ten training images were manually cropped for the purpose of examining their colour distribution. Fig. 2 shows two samples of the skin-cropped training images.

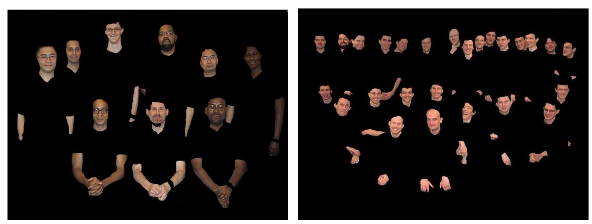


Figure 2. Skin-cropped training images

3.2. Skin Colour Subspace Analysis

The prepared skin colour samples were analysed in the RGB, HSV and YCbCr spaces, As opposed to 3-D space cluster approximation used by Garcia and Tziritas [12], we intend to examine 2-D colour subspaces in each of the mentioned colour models, i.e. H-S, S-V, H-V and so forth, to model the skin clusters more compactly and accurately.

In RGB space, the skin colour region is not well-distinguished in all 3 channels. A simple observation of its histogram will show that it is uniformly spread across a large spectrum of values.

In HSV space, the H (Hue) channel shows significant discrimination of skin colour regions, as observed from the H-V and H-S plots in Fig. 3 where both plots exhibited very similar distribution of pixels. In the hue channel shown in Fig. 4, most of the skin colour samples are concentrated around values between 0 and 0.1 and between 0.9 and 1.0 (in a normalized scale of 0 to 1).

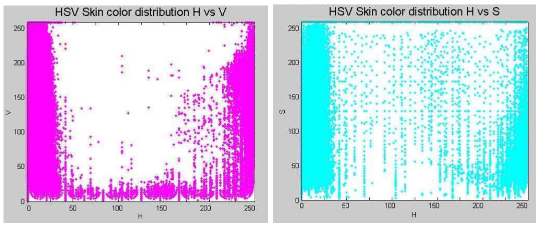


Figure 3. H-V and H-S subspace plots

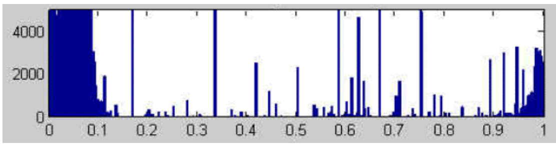


Figure 4. Distribution of the H (Hue) channel

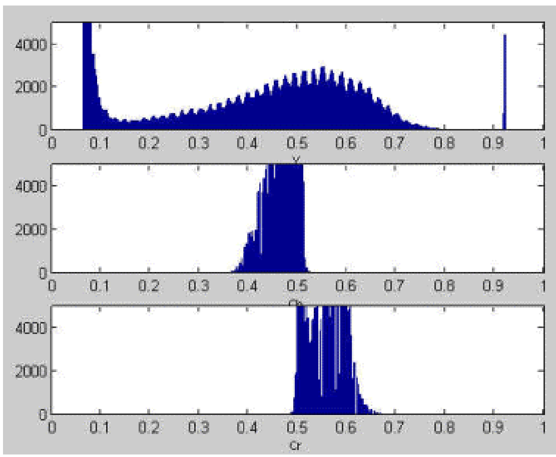


Figure 5. Distribution of Y, Cb and Cr

Some studies have indicated that pixels belonging to skin regions possess similar chrominance (Cb and Cr) values. These values have also been shown to provide good coverage of all human races [8]. Our analysis of the YCbCr space using our training set further substantiates these earlier claims, and have shown that the Cb-Cr subspace offers the best discrimination between skin and non-skin regions. Fig. 5 shows the compact distribution of the chrominance values (Cb and Cr) in comparison with the luminance value (Y).

It is also observed that the varying intensity values of Y (Luminance) does not alter the skin colour distribution in the Cb-Cr subspace. The luminance property merely characterises the brightness of a particular chrominance value.

3.3. Skin Colour Bounding Rules

From the skin colour subspace analysis, a set of bounding rules is derived from all three colour spaces, RGB, YCbCr and HSV, based on our training observations. All rules are derived for intensity values between 0 and 255.

In RGB space, we use the skin colour rules introduced by Peer et al. [11]. The skin colour at uniform daylight illumination rule is defined as

$$(R > 95) \text{ AND } (G > 40) \text{ AND } (B > 20) \text{ AND } (\max\{R, G, B\} - \min\{R, G, B\} > 15) \text{ AND } (|R - G| > 15) \text{ AND } (R > G) \text{ AND } (R > B) \quad (1)$$

while the skin colour under flashlight or daylight lateral illumination rule is given by

$$(R > 220) \text{ AND } (G > 210) \text{ AND } (B > 170) \text{ AND } (|R - G| \leq 15) \text{ AND } (R > B) \text{ AND } (G > B) \quad (2)$$

To consider both conditions when needed, we used a logical OR to combine both rule (1) and rule (2). The RGB bounding rule is denoted as Rule A.

Rule A: Equation(1) $\cup$ Equation(2) (3)

Based on the observation that the Cb-Cr subspace is a strong discriminant of skin colour, we formulated 5 bounding planes from its 2-D subspace distribution, as shown in Fig. 6. The five bounding rules that enclosed the Cb-Cr skin colour region are formulated as below:

$$Cr \leq 1.5862 \times Cb + 20 \quad (3)$$
$$Cr \geq 0.3448 \times Cb + 76.2069 \quad (4)$$
$$Cr \geq -4.5652 \times Cb + 234.5652 \quad (5)$$
$$Cr \leq -1.15 \times Cb + 301.75 \quad (6)$$
$$Cr \leq -2.2857 \times Cb + 432.85 \quad (7)$$

Rules (3) to (7) are combined using a logical AND to obtain the CbCr bounding rule, denoted as Rule B.

Rule B: Equation(3) $\cap$ Equation(4) $\cap$ Equation(5) $\cap$ Equation(6) $\cap$ Equation(7) (8)

In the HSV space, the hue values exhibit the most noticeable separation between skin and non-skin regions. We estimated two cutoff levels as our H subspace skin boundaries,

$$H < 25 \quad (9)$$
$$H > 230 \quad (10)$$

where both rules are combined by a logical OR to obtain the H bounding rule, denoted as Rule C.

Rule C: Equation(9) $\cup$ Equation(10) (11)

Thereafter, each pixel that fulfills Rule A, Rule B and Rule C is classified as a skin colour pixel,

Rule A $\cap$ Rule B $\cap$ Rule C (12)

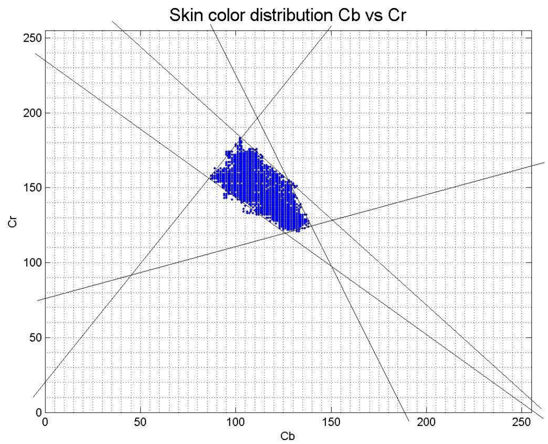


Figure 6. Bounding planes for Cb-Cr subspace

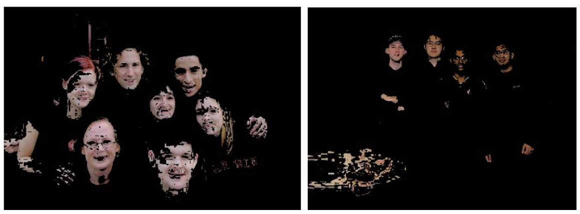


Figure 7. Skin segmentation using the RGB-H-CbCr model

3.4. Skin Colour Segmentation

The proposed novel combination of all 3 bounding rules from the RGB, H and CbCr subspaces (Equation 12) is named the "RGB-H-CbCr" skin colour model. Although skin colour segmentation is normally considered to be a low-level or "first-hand" cue extraction, it is crucial that the skin regions are segmented precisely and accurately. Our segmentation technique, which uses all 3 colour spaces was designed to boost the face detection accuracy, as will be discussed in the experimental results. Fig. 7 shows the skin segmentation result of two sample test images using the RGB-H-CbCr model.

The resulting segmented skin colour regions have three common issues:

a) Regions are fragmented and often contain holes and gaps.

b) Occluded faces or multiple faces of close proximity may result in erroneous labeling (e.g. a group of faces segmented as one).

c) Extracted skin colour regions may not necessarily be face regions. There are possibilities that certain skin regions may belong to exposed limbs (arms and legs) and also foreground and background objects that have a high degree of similarity to skin colour (also known as false alarms).

4. Morphological Operations

The next step of the face detection system involves the use of morphological operations to refine the skin regions extracted from the segmentation step.

Firstly, fragmented sub-regions can be easily grouped together by applying simple dilation on the large regions. Hole and gaps within each region can also be closed by a flood fill operation.

The problem of occlusion often occurs in the detection of faces in large groups of people. Even faces of close proximity may result in the detection of one single region due to the nature of pixel-based methods. Hence, we used a morphological opening to "open up" or pull apart narrow, connected regions.

Additional measures are also introduced to determine the likelihood of a skin region being a face region. Two region properties – box ratio and eccentricity are used to examine and classify the shape of each skin region.

The box ratio property is simply defined as the width to height ratio of the region bounding box. By trial and error, the good range of values lie between 1.0 and 0.4. Ratio values above 1.0 would not suggest a face since human faces are oriented vertically with a longer height than width. Meanwhile, ratio values below 0.4 are found to misclassify arms, legs or other elongated objects as faces.

The eccentricity property measures the ratio of the minor axis to major axis of a bounding ellipse. Eccentricity values of between 0.3 and 0.9 are estimated to be of good range for classifying face regions. Though this property works in a similar way as box ratio, it is more sensitive to the region shape and is able to consider various face rotations and poses.

Both the box ratio and eccentricity properties can be applied to the extracted skin regions either sequentially or parallelly, following a dilation, opening or flood fill.

5. Experimental Results and Discussion

The proposed RGB-H-CbCr skin colour model for skin region segmentation was evaluated on a face detection system using a test data set of 100 images, containing a total of 600 unique faces. In order to build this test data set, the images were randomly selected from the Internet[1], each comprising of two or more near-frontal faces and of a large variety of descent (Asians, Caucasians, Middle-Eastern, Hispanic and African). The test images also consist of various indoor

[1]All images taken from the Internet were used solely for this research only and there were no attempts to re-use, edit, manipulate or circulate these images for any other interests.

and outdoor scenes and of different lighting conditions – daylight, fluorescent light, flash light (from cameras) or a combination of them. The size of each image ranged from 500x350 to 1000x600, regardless of face size. The face detection system was implemented using MATLAB on a 2.4MHz Pentium IV machine running on 256 MB RAM.

To evaluate our experiments, we defined two performance metrics to gauge the success of our schemes. False Detection Rate (FDR) is defined as the number of false detections over the number of detections.

$$\text{FDR} = \frac{\text{false detections}}{\text{number of detections}} \times 100\% \tag{13}$$

Detection Success Rate (DSR) is defined as the number of correctly detected faces over the actual number of faces in the image.

$$\text{DSR} = \frac{\text{correctly detected faces}}{\text{number of faces}} \times 100\% \tag{14}$$

where the number of correctly detected faces is equivalent to the number of faces minus the number of false dismissals.

Table 1 shows the experimental results of the face detection system using various combination of morphological operations (as described in Section 4). The face detection system achieved a good detection rate of 90.83% using a parallel combination of opening, box ratio and eccentricity operators. Other combinations resulted in a poorer DSR or higher FDR.

The proposed scheme was also compared with the well-known AdaBoost face detector/classifier by Viola and Jones [13], and results showed that the proposed scheme (with the right configuration of morphological operators) is able to reach comparable standards to that achieve by the AdaBoost algorithm (90.17%) on the similar data set.

To evaluate the effectiveness of the RGB-H-CbCr skin colour model (Table 2), the face detection system was tested with various combination of colour models, each represented by its own set of bounding rules. The combination of all 3 subspaces resulted in the best DSR and lowest FDR values. Fig. 8 presents some sample results of the proposed face detection system.

As shown in the experimental results, the proposed method sometimes failed to detect a face correctly, as seen from the high FDR of 28.29% (Table 1). This could be attributed to the usage of morphological operators. Though these operators are used parallelly to improve the likelihood of detecting faces, it may sometimes cause “over-detection” of faces. Fig. 8(b) and Fig. 8(c) show examples of false detections and false dismissals encountered in our experiments.

Table 1. Face detection experimental results

Method	FDR (%)	DSR (%)
Opening+BoxRatio+Eccentricity (parallel)	**28.29**	**90.83**
AdaBoost [13]	18.65	90.17
Opening+BoxRatio	20.76	87.17
Opening+Eccentricity	23.73	85.17
Dilation+Opening	42.29	83.00
Opening+BoxRatio+Eccentricity (sequential)	13.36	82.17

Table 2. Results using various combination of colour model bounding rules

Method	FDR (%)	DSR (%)
RGB only [11]	43.05	69.00
RGB+CbCr	36.14	77.17
RGB+H	33.82	83.50
RGB+H+CbCr	**28.29**	**90.83**

The RGB-H-CbCr skin color model is able to deal with various brightness and illumination conditions, but it remains susceptible to detection of non-skin objects that possess similar chrominance levels as skin colour.

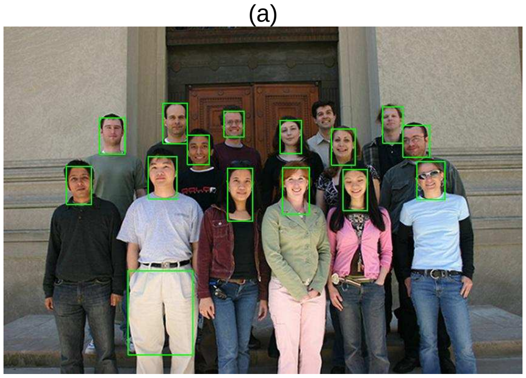
Occlusion remains a difficult problem to tackle, especially when colour is used as the cue for segmentation. Occluded faces and faces that are closely located are often merged together by a minute portion of a connected skin part. Fig. 8(d) shows an example of misclassification of multiple persons due to occlusion.

6. Conclusion

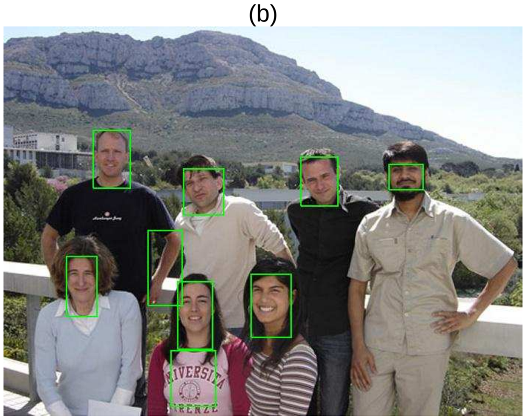
In this paper, we have presented a novel skin colour model, RGB-H-CbCr to detect human faces. Skin region segmentation was performed using a combination of RGB, H and CbCr subspaces, which demonstrated evident discrimination between skin and non-skin regions. The experimental results showed that our new approach in modelling skin colour was able to achieve a good detection success rate. On a similar test data set, the performance of our approach was comparable to that of the AdaBoost face classifier.

In future work, we intend to refine the use of morphological operations in the post-processing of the extracted skin regions. An adaptive training (incremental learning) of the skin colour model can be used to improve the overall classification of skin regions. Primarily, the elimination of false detections and false dismissals is crucial to the success of a robust face detector.

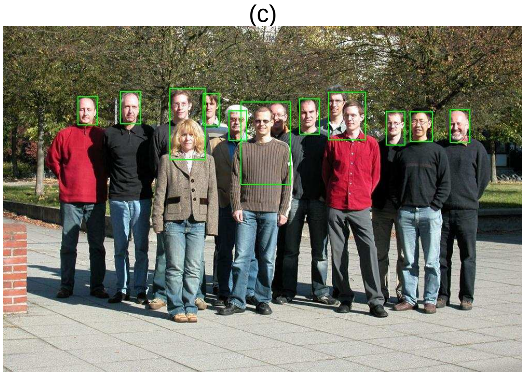
(a)



(b)



(c)



(d)

Figure 8. Sample face detection results using the test data set

7. References

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