Face Extraction using 2D Color Histograms

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Abstract: **Face extraction is first step of many applications including surveillance and security, human-machine interfaces, object-based video coding, virtual reality, automatic 3-D modeling and image database management. In this work we propose a face detection algorithm for color image sequences in presence conditions of varying lighting conditions and complex background. Our method finds skin regions and then generates face pixel candidates based on a histogram analysis of color space. The algorithm constructs face color map for verifying face pixels. The proposed approach consist thee parts: a color space selection, a modeling human skin with probability distribution and a human skin segmentation to identify probable regions corresponding human faces.**

Keywords: **Color space, 2D Color Histograms, Face detection**

I. Introduction

The analysis of human face images receives more interest in the field of image processing. The task of facial image analysis includes the face extraction and localization, the recognition of face and the analysis of facial expression or human mimics. Face detection is needed as preprocessing step for many applications, including surveillance and security, human-machine interfaces, object-based video coding, virtual reality, and automatic 3-D modeling. In addition, the robust face extraction is the first important step in a fully automated facial analysis system for static images and video sequences. There are many variations of image appearance such as pose variation (front and profile), occlusion, image orientation, lighting condition and facial expression [1], [2], which would bother face analysis and would be taken into account.

Various approaches to face detection are discussed in [1], [2], [3], [5]].

One of difficult problems in skin color detection is color constancy. Ambient light and shadows change the apparent color of an image. Different cameras affect the color value as well. A majority of skin detection algorithms in color image sequences use color histograms for segmentation [1], [2]. This approach relies on the assumption that skin colors form a cluster in same color measurement space.

In this work we propose an approach to automatic detection of faces in color image sequences. The proposed approach consists of three parts: a color space selection, a modeling human skin with probability distribution (2D histograms) and a human skin segmentation to identify probable regions corresponding human faces.

The paper is organized as follows. In the following Section (II.A) the choice of suitable skin color space is described. In Section II.B the use of 2D histograms in two variant - pixel-based skin color detection and face location using regional histogram ratio is discussed. The face skin color segmentation is given in Section II.C. The human skin segmentation employs a model-based approach to represent and differentiate the background colors and skin colors. Experimental results evaluating the performance of the algorithm are given in Section III.

II. Mathematical Description

A. Color space selection

Color information is an important feature of human faces. Using skin color as a feature for detecting face skin regions has several advantages. In particular, processing color is faster than processing other facial features. The more so as color information is invariant to face geometrical transformations. However, even under a fixed ambient lighting, people have different skin color appearance, but human skin forms a relatively tight cluster in color space[1].

Furthermore, to successfully use skin color for face detection, we need to choose color space, in which human skin colors cluster tightly together and reside remotely to background color[1], [2]. Color space is a method of color information obtained for a still image and video sequences. Human skin color tends to cluster in different color spaces. Different color spaces tend to enhance characteristics of images on expense of others[1], [3], [4]. Some color spaces are discussed in this paper.

The color space RGB (or the normalized color space RGB) is one of most widely used color spaces for processing and storing of digital image data [2], [3], [4]. However, high correlation between the color components, mixing of the chrominance and the luminance data make RGB color space not very favorable choice for color analysis and recognition.

In the color space YCbCr, the color is represented by luma, constructed as a weighting sum of RGB values, and two color difference values Cb and Cr that are formed by subtracting luma from RGB red and blue components [3], [4]. The transformation simplicity and explicit separation of luminance and chrominance components make this color space very attractive for skin color modeling.

The family of color spaces HSI (V, L) – Hue, Saturation, Intensity (Value, Lightness) was introduced when there was a need for the user to specify color properties numerically [2]. *Hue* defines the dominant color of an area; *saturation*

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measures the colorfulness of an area in proportion to its brightness. The “intensity”, “lightness” or “value” is related to the color luminance. The explicit discrimination between luminance and chrominance components made this color spaces popular for skin color segmentation. Besides YCbCr color space, several other linear transform of the RGB color space was employed for human skin detection – YES, YUV and YIQ [2], [5].

Many works on face skin detection discard the luminance component of the color space. This decision seems logical, because this is a dimensionality reduction. The goal of any color-based approach is diminishing the influence of the lighting conditions. The chrominance-only color analysis will make the approach partially independent from the lighting conditions.

We choose YCbCr as the processing color space since it is perceptually uniform and separate the luminance and the chrominance components. In our implementation only the CbCr components are used to model the distribution of skin colors. The YCbCr space is of particular interest because it is widely used in still-images and video coding standards such as JPEG, MPEG, and H.263.

B. Modeling human skin with 2D histograms

The purpose of skin color modeling is to build a decision rule that will discriminate between skin and not-skin pixels. The techniques for skin color modeling in YCbCr space can be classifies into following categories: parametric, non-parametric, and semi-parametric. A parametric skin color model has a specific functional form [1], [2], [6] with adjustable parameters chosen to fit the model to the input data. A non-parametric model does assume any particular form (histogram thresholding) [5]. A semi-parametric approach applies a very general form with adaptive parameters systematically varied in number as well as in value in order to create flexible models [7].

Color histogram is the typical method to describe the distribution of chromatic component in the specified image. Histograms are created by equally by subdividing the color space (YCbCr) into a number of bins, and then counting the number of pixels falling into each of the bins. We choose a 2D histogram (Cb, Cr) to represent the skin tones. By using two parameters (Cb,Cr) of color system, which do not correspond to intensity or illumination, the histogram should be more stable with respect to differences in illumination and local variations caused by shadows.

Let a vector $\vec{C}$ = [Cb, Cr]^t represent a color pixel at spatial position (i,j) with chromatic components Cb(i,j), Cb(i,j)) be a color vector in a color space YCbCr. Let P(C/skin) and P(C/nonskin) be the conditional probability density functions of skin and nonskin color clusters. The color vector C is classified as skin color if

$$\frac{p(\vec{C} / skin)}{p(\vec{C} / nonskin)} \geq \Theta \qquad (1)$$

where Θ is a threshold. The left term is known as the likelihood ratio [12]. The theoretical value of Θ that minimizes the classification cost is determined by a priori probabilities P(skin) and P(nonskin). The probability P (skin) of obtaining skin pixels in the image is approximated by the fraction of pixels known to be skin

$$P(skin) = \frac{T_s}{T_t}, \qquad (2)$$

where Ts and Tt are total pixel counts contained in the skin regions and the whole image, respectively.

The threshold Θ can be computed from

$$\Theta = \frac{\lambda_f \; P(nonskin)}{\lambda_{rj} \; P(skin)}, \qquad (3)$$

where λd and λr are the cost of false detection and false rejection. The cost of correct classification [8] is assumed to be zero, but the value of Θ can be computed experimentally. Since the skin color and the nonskin color models are disjunctive to each other, the priori probability P(nonskin) can be computed from P(nonskin) = 1- P(skin).

Bayes rule states that the probability of skin given a color vector is

$$p(\vec{C} / skin) = \frac{H_{skin}(\vec{C})}{T_s} = \hat{H}_{skin}(\vec{C}), \qquad (4)$$

$$p(\vec{C} / nonskin) = \frac{H_{nonskin}(\vec{C})}{T_{ns}} = \hat{H}_{nonskin}(\vec{C}), \qquad (5)$$

$$p(skin / \vec{C}) = \\ = \frac{p(\vec{C} / skin).P(skin)}{p(\vec{C} / skin)P(skin) + p(\vec{C} / nonskin)P(nonskin)} \approx \\ \approx \hat{H}_{ratio}(\vec{C}) \approx \frac{\hat{H}_{skin}(\vec{C})}{\hat{H}_{total}} \qquad (6)$$

The analysis in this subsection show, that Bayesian skin color model can be applied to any color space with good result.

There are some problems related with the histogram using for a color analysis. Firstly, it’s the change of illumination condition or influence of noise. Secondly, it cannot preserve spatial information. The other problem is that it required large feature vector and it is very important to simplify the histogram in some way. A color histogram used as a descriptor should be small enough to be managed, but it should produce correct results.

In other side, there are images with different content and chrominance but with equal or similar histograms.

There are several color features available. The color moments are proposed as color descriptor consisting of average, variance, and third-order moment. But it is difficult to evaluate these features and it is not possible to use them during real time processing.

Our approach employs a 2D color histogram H = [h(Cr,Cb)] for modeling skin color in Cb-Cr color space. After initial step - filtration and normalization of input face images, it is computed the average 2D histogram of 30 faces (training set), which was used to create a common skin classifier working for all kinds of skin. Training is an off-line procedure that does not affect the on-line performance. Nevertheless, it is a time-consuming process in a sense that a human operator should manually mark all skin-colored pixels in the chosen training set. To obtain a training set that is capable of supporting detecting of various skin tones in images acquired from different cameras requires a large training set.

There are a few algorithms for modeling human skin with 2D histograms: “chromatic” *thresholding*, *histogram Lookup Table* and *histogram ratio Lookup Table.*

“Chromatic” Thresholding. A method that is often used and easy to implement is thresholding one or several channels of a color space with one or several thresholds, e.g., in the CbCr plane. This method used a minimum and maximum Cb and Cr components, respectively, i.e., define a skin region in YCbCr color space, it use two thresholds for Bayes classification.

Let Cb_{min}, Cb_{max} and Cr_{min}, Cr_{max} are minimum and maximum thresholds, respectively for chromatic components Cb and Cr in 2D average color histogram. The classification rules determine a rectangular area in CbCr chromatic plane.

The segmentation is obtained for current skin color vector $\vec{C}$ = [Cb, Cr]^t as $\vec{C} \in O_{bj}$ if are performed the conditions simultaneous $\begin{cases} C_b(ij) \in [C_{b\min}, C_{b\max}] \\ C_r(ij) \in [C_{r\min}, C_{r\max}] \end{cases}$,

here O_{bj} is segmentationed color region (face).

The thresholds are calculated from 1D color histograms for Cb and Cr color components. In the segmented areas faces are detected with limited color space. The skin area that is classified as a face is that used to calculate new thresholds that are adapted to that particular face these thresholds are then used to segment the face during tracking. The obvious advantage of this method is a simplicity of skin detection rules that conducts to a construction of very rapid classifier.

Histogram Ratio Lookup Table. This approach realizes a face location using a ratio of two 2D histograms. The main idea is localization of known face image in a known background based on colors. Let we determine the average color 2D histograms for face training set

Ho = [ho(Cr,Cb)] and for the background Hg = [hg(Cr,Cb)]. That the ratio of histograms is

$$R_{c_r c_b} := \min\left\{\frac{h_o}{h_g}, 1\right\} \qquad Cb, Cr=0,255,$$

with $$RH = \frac{H_0}{H_g} = \left[R_{c_b c_r}\right] \qquad (7)$$

C. Skin color segmentation

In order to detect a skin color region we must map the skin pixels into a region. Generating of skin/non-skin maps strongly depends on lighting conditions and the tuning of the camera. This is supported by the histograms of the normalized maps of expected skin regions, shown on Fig.5 and Fig.6**.**

III. Experimental Results

Photos are usually taken under various lighting conditions. This is the reason why they have variations in quality, color, position, pose and facial expression. Our algorithm has been evaluated on various images from the World Wide Web. We present the evaluation on a set of images from our local database. The experiment took place in the following steps. First, a training set of skin samples is loaded, shown on Fig.2. Next, the sequence of original images is shown on Fig.1 and background Fig.3. After finding the optimal threshold value for every image we obtained a mask of the expected skin region, Fig.4. Using the mask we extract the expected skin region, ingnoring the non-skin regions of the image, as can be seen on Fig.4. Finally we use the limited region of the skin to search for facial features, with the algorithm described the previous section.

IV. Conclusion

We have presented a method for face detection in frontal images and feature extraction from a detected face region. First of all, our method generates a mask of authenticity of face region in the image. We use two algorithms of generating the mask. After generating an optimal mask, the face region is being extracted from the original image.

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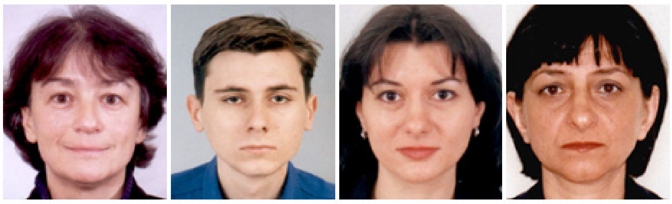

Fig.1 Original images of faces

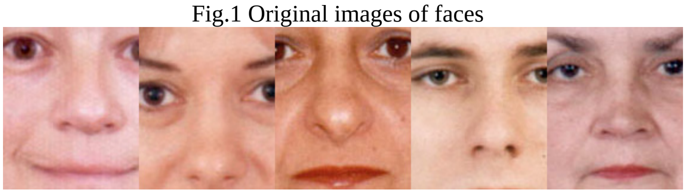

Fig.2 Experimental training set of faces

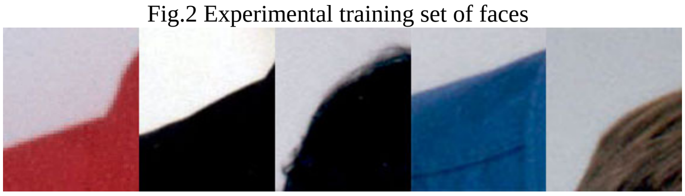

Fig.3 Original images of background

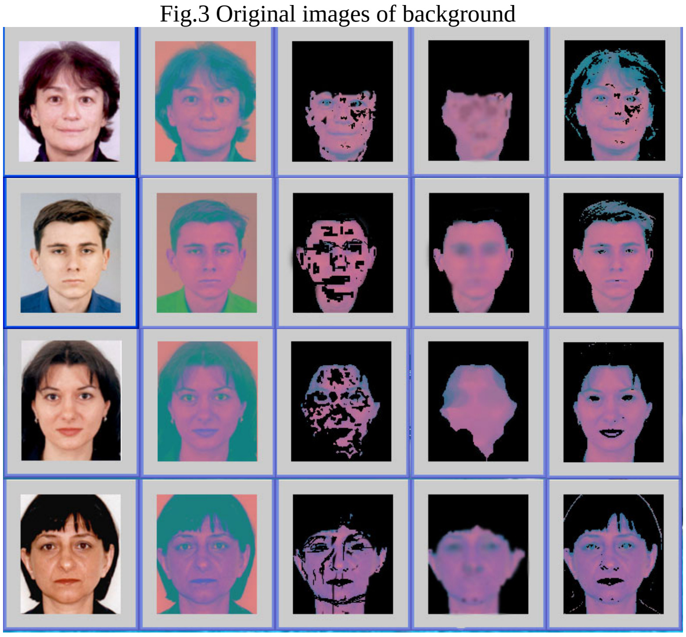

Fig. 4 Original images (RGB), Original images (YCrCb), Mask without smoothing, Mask after morphological filtering, Mask with smoothing;

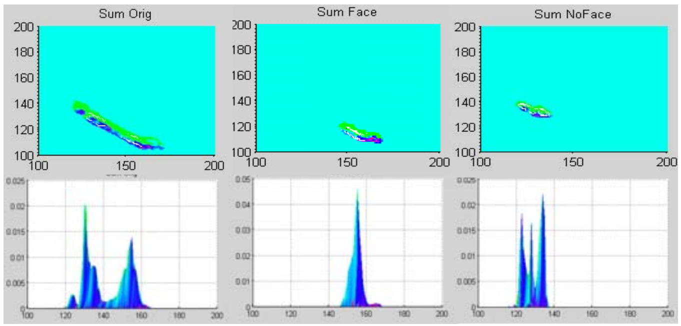

Fig.5 Histograms of original images, faces and background of training set

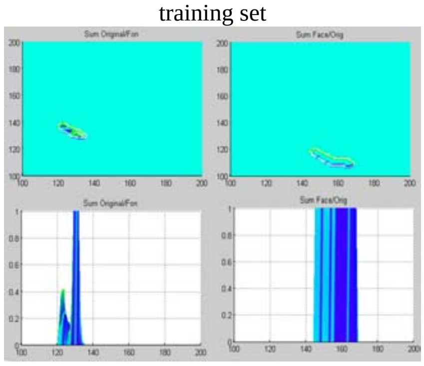

Fig.6 Histogram ratio of Faces/Background and Faces/Original images