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Component-Based Face Detection in Color Images

Ali Atharifard and Sedigheh Ghofrani

Department of Electrical Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran

Abstract: Face detection is an important topic in many applications. To analyze the information included in face images, a robust and efficient face detection algorithm is required. Variation of illumination and pose in addition to existence occlusion and orientation decrease the algorithm performance. These factors change global facial appearance while face components are less affected by these factors. Using component-based method, we can overcome the referred problems. In this paper, a component-based face detection algorithm using color feature is proposed. In this method, skin color regions are segmented in transformed color spaces as the candidate faces. Then the most important facial features, eyes and mouth, are localized as necessary components in face candidate regions. In order to localize the facial features two new maps are proposed. To confirm each candidate face as a face, a flexible geometric model is used. This model by construction of a triangle between detected facial components verifies the existence of the face. Our proposed method is even able to localize occluded facial features. In this method, by combination of reliable component detectors and considering the logical geometric relation between facial components, in addition to high detection rate, the algorithm has a low alarm rate. Furthermore we can detect not only single face but also multiple faces in an image.

Key words: Face detection · Skin color segmentation · Facial feature detection · Flexible geometric model

INTRODUCTION

Human face detection is the first step of any face processing systems, computer vision and computational image analysis. The last decade has shown dramatic progress in this area, with emphasis on such applications as human computer interaction, biometric analysis, content-based coding of images and videos, content-based image retrieval systems, robotics vision and surveillance systems. In reality, most images are complicated and may contain extraneous visual information or multiple faces. Given an image, the goal of a face detection algorithm is to identify the location and scale of all the faces in the image [1]. Face detection is impacted by lots of external and internal factors. Even if a subject's face is stored in the database, a disguise or even a minor change in appearance, like wearing sunglasses or growing a mustache can often fool the system. Also an unusual facial expression can confuse the software. Different illuminations deform faces significantly. There are several algorithms available in the literature that try to solve these problems. A survey on face detection with more than 150 references appears in [2]. Face detection methods are classified into four categories:

1) Knowledge-based methods. In these rule-based methods usually the rules consider the relationships between facial features. For the first time, Yung and Huang [3] used a hierarchical knowledge based method to detect faces. Their system consists of three level of rules. Although it did not result in a high detection rate, one attractive feature of this method was the coarse-to-fine or focus-of-attention strategy to reduce the required computation. 2) Feature invariant approaches. The purpose of these algorithms is finding structural features that work even when the pose, viewpoint, or lighting condition vary and use them to locate faces. Some of these features are texture, color, grouping of edges, or compound of them. One problem with these feature based algorithms is that, the image features can be severely corrupted due to illumination, noise and occlusion [4]. 3) Template matching methods. In these methods, several standard patterns of face are stored to describe the face as a whole or the facial features separately. The existence of a face is determined based on correlations between an input image and the stored patterns. The advantage of this approach is being simple to implement, but it cannot effectively deal with variations in scale, pose and shape [5].

Corresponding Author: Sedigheh Ghofrani, No. 9, 14th Street, Pakistan Street, Shahid Beheshti Street, Pars Gostareh, 15317 (1531764611), Tehran, Iran. Tel: +98-21-88731446, Fax: +98-21-88532683, E-mail: ali_atharifard@yahoo.com & s_ghofrani@azad.ac.ir.

4) Appearance-based methods. In contrast to template matching, in these methods, the models are learned from a set of training images which should capture the representative variability of facial appearance [6]. These methods are based on learning algorithms. Several algorithms have been proposed for skin color pixel classification. They include piecewise linear classifiers [7], the Bayesian classifier with the histogram technique, [8], [9], Gaussian classifiers [10-12] and the multilayer perceptron [13]. these methods have good results, they are strongly rely on training set.

Recently, component-based approaches have produced better results than global approaches; since individual components vary little while the variation related to pose changes are mainly geometric [14]. Component detectors can accurately locate facial components and component-based approaches can be used to construct detectors that can handle partial occlusions [15]. The majority of the previously proposed component-based methods used gray level values to detect faces in spite of the fact that most images today are color. As a consequence, most of these methods are computationally expensive and some of them can only deal with frontal faces with little variations in size and orientation. To solve these problems, a color-based approach has been studied. It segments skin-like regions and then detects or verifies the presence of facial areas in these regions [14]. However, it is computationally expensive due to its complicated segmentation algorithm and time-consuming wavelet packet analysis. In color images, [1] proposed a component-based face detection algorithm that constructs eye, mouth and boundary maps to verify candidate faces. The facial components were detected using feature maps derived from models based on skin color and were combined based on the geometries and orientations of the detected components. Since this procedure used simple geometrical relations, the system may be limited in terms of flexibility.

In this paper, we propose novel component-based face detection for nearly frontal face images. This approach is constructed by combination of knowledge-based and feature invariant methods. Color feature is able to handle a wide range of variations in static color images. Our approach models skin color using a parametric elimination in three components of transformed color spaces that are strong to separate the skin tones from non-skin pixels. This method extracts facial features by using two new feature maps for the eyes and mouth. In addition, we propose a flexible geometric model to minimize the false alarm rate in facial feature detection.

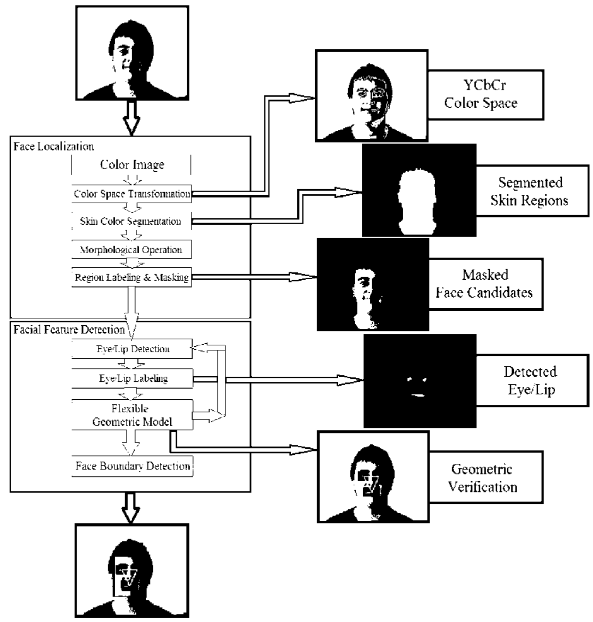


Fig. 1: Proposed face detection algorithm

The paper is organized as follow. Section 2 describes the face detection algorithm. Section 3 presents detection result of our algorithm on a standard face database. Conclusion is described in section 4.

Face Detection Algorithm: The procedure of our component-based algorithm for face detection and verification is shown in Fig. 1. The algorithm includes two major modules: 1) localizing face candidates by using skin color segmentation, 2) verifying the candidate regions as faces by using geometric relations between detected facial features. At first, the RGB color space is transformed in the YCbCr, HSV and the normalized RGB color spaces. The skin tone pixels are extracted using a skin color model constructed of transformed color components. The detected skin tone pixels are iteratively segmented into connected components by using color variance. After applying a combination of morphological operations, face candidates are grouped. Employing only skin color segmentation, would have a considerable false alarm rate (FAR). In general, detectors can make two types of errors: false negatives in which faces are missed resulting in low detection rates and false positives in which an image region is declared to be face, but it is not. A fair evaluation should take these factors into consideration; since a method can tune the parameters to increase the detection rate while also increasing the number of false detections. In order to minimize these undesired factors, we extract the most important face components, the eyes and mouth. After localizing the eyes and mouth and checking their geometric relation, the component-based algorithm automatically labels those candidates that contain the facial features with the correct relation and removes the other regions.

Color Space Transformation: Skin detection is the first stage for detecting faces in an image and it can be performed by using color models named RGB, YCbCr, HSV, YIQ, YUV, CIE, XYZ, etc. An efficient skin detection algorithm can detect skin irrespective of being different skin colors (brown, white, black) and varying lighting condition [16]. In this section we explain briefly the RGB, HSV and normalized RGB and their advantages and disadvantages to find appropriate maps for our work. RGB color space is the most common color space, but R, G and B are dependent on illumination conditions. For this reason skin detection with RGB color space can be unsuccessful when the illumination conditions change. YCbCr color model belongs to the family of television transmission color models, where Y is the luminance component and Cb and Cr are related to the blue and red chrominance components, respectively. The following nonlinear conversion is used to segment the RGB image into Y, Cb and Cr components:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.5 \\ 0.5 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \quad (1)$$

In HSV (Hue-Saturation-Value) color space, hue is generally related to the wavelength of the light, so it shows significant discrimination of skin color regions; value shows illumination and saturation is a component that measures the colorfulness. Conversion between RGB and HSV color spaces is as follow:

$$H = \begin{cases} 2-\cos^{-1}\left(\dfrac{(\text{R-G})+(\text{R-B})}{2\sqrt{(\text{R-G})^2+(\text{R-B})(\text{G-B})}}\right); & B > G \\ \cos^{-1}\left(\dfrac{(\text{R-G})+(\text{R-B})}{2\sqrt{(\text{R-G})^2+(\text{R-G})(\text{G-B})}}\right); & \text{O.W} \end{cases}$$

$$\text{S}=1-\frac{3\times\min(\text{R,G,B})}{\text{I}}$$

$$\text{V} = \max(\text{R,G,B}) \quad (2)$$

Normalized RGB space is formed to achieve lower dependency on lighting variations. The red, green and blue components of normalized RGB space can be obtained from the three components of RGB space using the simple following equations:

$$r = \frac{R}{R+G+B};\ g = \frac{G}{R+G+B};\ b = \frac{B}{R+G+B};\ r+g+b = 1 \quad (3)$$

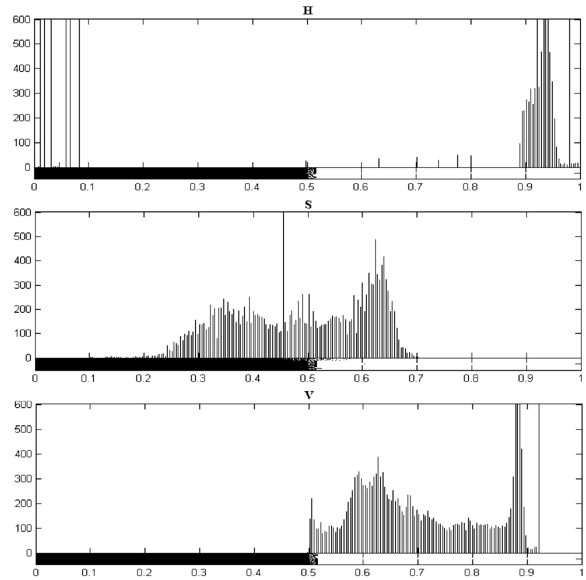


Fig. 2: Comparison the compactness of H, S and V histograms for a sample skin region

We will use r and g component to implement our new lip detection model (section 2.3.2).

Skin Color Segmentation: Skin detection is an important first step in many intelligent systems such as face detection and recognition and face and hand tracking systems. Many skin detection, various skin color detection models such as skin color region, statistical diagram model and Gaussian model have been proposed [9, 12, 17]. The basis of skin region model is that human skin color can be clustered in a limited region. It was observed that the skin color region in all 3 channels of RGB color space is not well distinguished [18]. In other words, histogram of the three channels in RGB color model show uniformly spectrum values spreading. So, in this paper the skin color images are analyzed in the HSV and YCbCr color spaces. The histogram of H, S, V and Y, Cb, Cr for a sample skin region are sketched in Fig. 2 and Fig. 3. In addition, YCbCr color space distribution are depicted in Fig. 4. By experiment, Chai *et al*. [18-20] found that any skin pixel satisfies (4) in YCbCr color space:

$$77 < Cb < 127;\ 133 < Cr < 177 \quad (4)$$

As it can be seen in Fig. 2, H component of skin color is perfectly concentrated between 0-0.09 and 0.9-1 values. We found that the combination of these three ranges on Cb, Cr and H components can perfectly cover extraction of skin pixels of all races and ethnic groups and

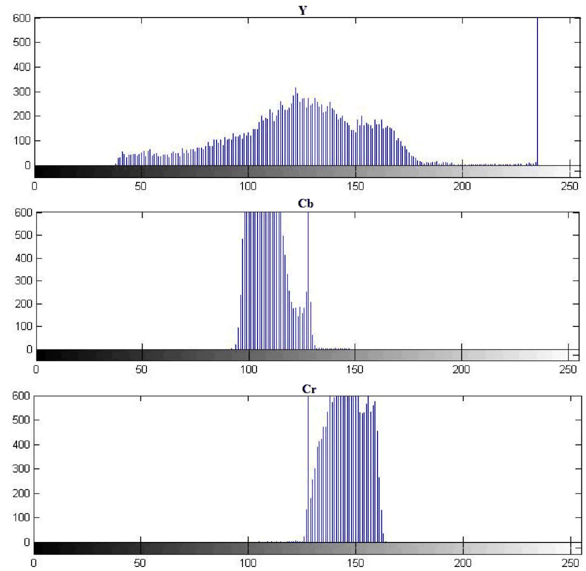


Fig. 3: Comparison Y, Cb and Cr histograms for a sample skin region Clearly showes Cb and Cr histograms are more compact than Y histogram.

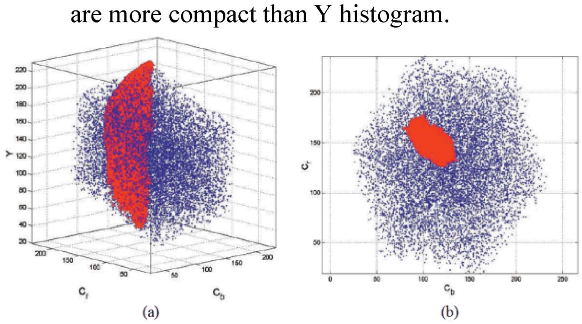


Fig. 4: (a) The YCbCr color space distribution and (b) 2D projection in Cb-Cr subspace (blue dots represent all colors in a sample image while red dots represent the skin color distribution). In skin regions, Cb and Cr components are more compact than Y component

even faces wearing makeup. Thereby, Cb, Cr and H components are able to separate skin and non-skin pixels. In this paper, we extract skin color pixels by using these three components from YCbCr and HSV color spaces. Then, we employ morphological filtering in order to remove existence noise and mask the skin color. Skin color segmentation omits non-skin regions from the images, so next processes are just performed on these regions including uncovered parts of the body and probably other skin-like regions. This segmentation leads to an effective computationally reduction. Procedure of our skin color detection method on three selected images from CVL database [21] is shown in Fig. 5. They have chosen because of existing beard and mustache

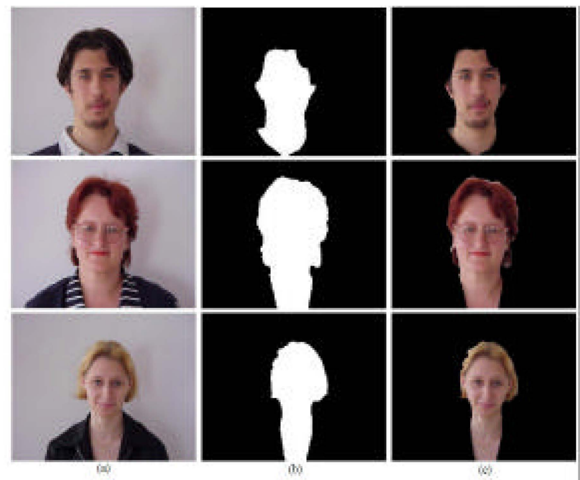


Fig. 5: (a) selected sample images from CVL database, (b) face mask obtained from the proposed skin color model after applying morphological operations, (c) masked face. Unfortunately, there are some false detection in hair regions

(first photo), wearing glasses and make-up (second photo) and large amount of uncovered skin region (third photo). So there are challenges for detecting the face accurately.

Localization of Facial Features: In general, component-based face detection approach provides appropriate performance whereas occlusion is existed or pose and illumination are changed. Implementation a robust face detection algorithm with perfect accuracy and low false alarm rate needs verification the candidate faces based on facial features location. Among various facial features, eyes and mouth are the most prominent features [22]. In general, in each face there are two eyes and a mouth or two lips which should be localized. The most applications are template-based [23]. However we directly localize eyes and mouth based on their feature maps derived from two new models. Our proposed maps for eyes and mouth localization are described in following.

Eye Map: The eye detection model in YCbCr color space that was proposed by Hsu *et al*. [1] contained two maps constructed using chrominance and luminance components. They found that, the Cr color component has weak response around the eye regions, while the Cb component has a strong value in these areas, so They defined the chrominance map (EyeMapC) as follows:

$$\text{EyeMapC} = \frac{1}{3}\{(Cb)^2 + (255\text{-}Cr)^2 + (\frac{Cb}{Cr})\} \quad (5)$$

Where $(Cb)^2$, $(255\text{-}Cr)^2$ and $(\frac{Cb}{Cr})$ all are normalized to the range [0-255]. The EyeMapC result was then dilated and masked.

We also found that histogram processing has a good effect on localizing eyes, so that equalizing Cb color component leads to strong value especially in eye regions and conversely causes weak response in other face regions. So, we can extract the eye regions from an image just from two chrominance components of YCbCr color space. Therefore our EyeMap is constructed from combination of EyeMapC [1] and equalized Cb in histogram using an AND operation. Our EyeMap is achieved as below:

$$EyeMap = EyeMapC \text{ AND } HistEq(Cb) \quad (6)$$

The eye map result is then dilated, masked and normalized to brighten both the eyes and suppress other facial areas, as shown in Fig. 6. By using (6) and considering reasonable position of eyes in the face (section 2.3.3), the false alarms are decreased.

Lip Map: Referring to previous researches, there are lack of mouth detection results specifically dealing with thick beard, mustache and open mouth. Lips color region contains a strong red component and weak blue and green component in comparison with the other facial regions. We found that lips color have a strong intensity in normalized R space while they have weak response in normalized G space; so we use these points to built a new mouth map. Our proposed map for lip localization is written as follow:

$$LipMap=(\frac{r}{r+g})^2 \quad (7)$$

Where r and g are normalized to the range [0-1]. After using morphological filtering on LipMap, result is then masked. Our experimental results show that the proposed algorithm detects lips perfectly even for open mouth. Fig. 7 Shows the construction of mouth map by our suggested model.

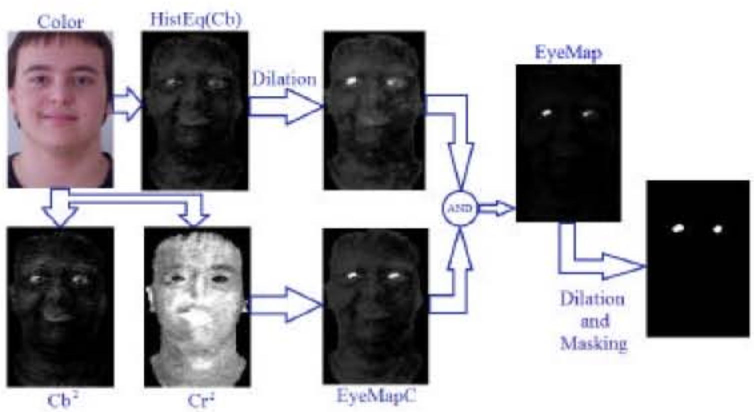


Fig. 6: Construction of eye map

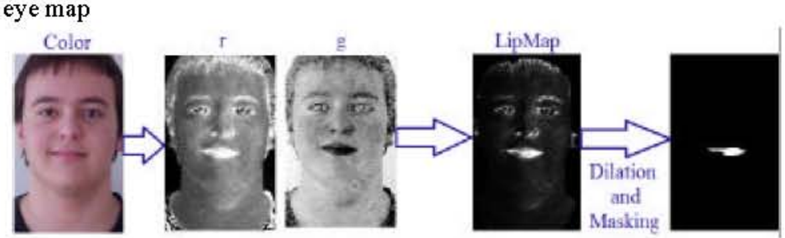


Fig. 7: Construction of mouth map

Fig. 8: Flexible component-based face model: (a) a schematic template of a frontal face with two eyes, a lip and their relations, (b) a frontal face in the image plane for face detection, (c) a flexible template of relations with uncertainty which a line means a center of the relation and uncertainty is shown with a gray area [24]

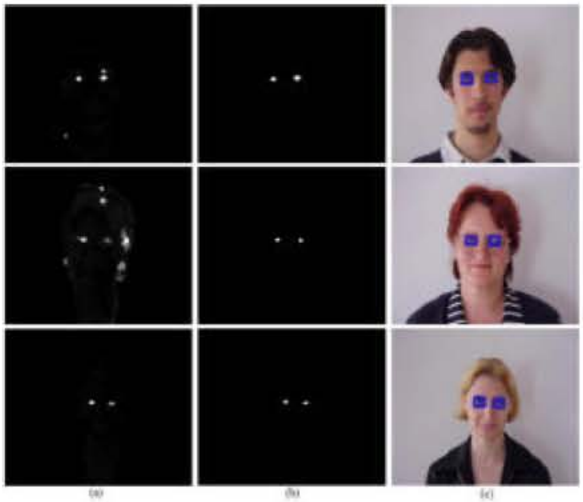


Fig. 9: (a) extracted eye candidates by proposed EyeMap (Eq. 6), (b) segmented eyes after verification by using flexible geometric model and morphological operation, (c) eye labling on input images

Flexible Geometric Model: After finding eyes and lips candidates as face components, the algorithm uses a flexible component-based face model to detect faces based on their geometrical relations [20]. Each step for detection and verification updates the corresponding templates and their relations. A template for a frontal face, which was obtained by averaging location of facial components and their relations is shown in Fig. 8(a). The flexible template used for determining the relations of components is shown in Fig. 8(c). It contains both averages and uncertainty areas. Such a flexible component-based face model allows flexibility in terms of facial descriptions. Fig. 8(a-c) is an example for detection with two eyes, a lip and their relations. The relationship between features can be presented by their relative distance and positions. In a frontal face image, a face often appears with two eyes that are symmetric and a mouth that has located between eyes and vertically downer than the eyes. In addition, the eyes are located in upper part and the mouth is located in downer part of the face region. By using the flexible geometric model and mentioned considerations the extra candidates are omitted and just the final facial features are labelled. The eyes and mouth localization results are demonstrated in Fig. 9 and Fig. 10 respectively. These Figures show that how the flexible geometric model followed by morphological filtering eliminate the wrong candidates of features. As it can be seen in Fig. 9, even under occlusion (wearing glasses) we have succeeded to localize the eyes. Also the lip model could extract the mouth regions for faces wearing makeup and with mustache (Fig. 10). To detect components and check relations using a component-based approach, Comparing with [7] which used AdaBoost for training, our face detection model uses on-line learning that starts whenever a new data comes. Given a new image, after detecting components, the proposed algorithm detects faces using verification on its flexible geometric model. Such steps can be repeated to the sequence of images. Fig. 11 shows the final obtained results from our face detection algorithm for sample images in Fig. 5(a). We also found that mentioned geometric relation can be used to find even occluded or missed facial features. In this way the detection accuracy in dealing with partial occlusion will be increased. Face and facial features detection in an occluded face also are shown in Fig. 12. According to the flexible geometric model, our algorithm has found mouth region that had been occluded (Fig. 12(b).

Fig. 10: (a) extracted mouth candidates by proposed LipMap (Eq. 7), (b) segmented mouth after applying flexible geometric model and morphological operation, (c) mouth labling on input images

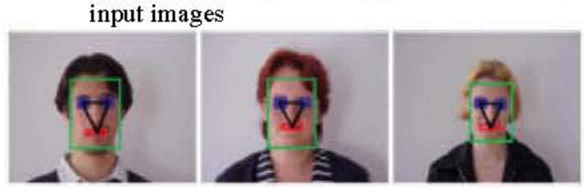


Fig. 11: Final face detection results after implementing feature triangle to confirm the face candidate as a face

Table 1: Experimental result of proposed method on CVL face database

Feature type	No. of features	Correctly detected features	False positive	False negative	Detection accuracy (%)
Face	342	334	2	8	97.66
Eye	684	657	34	27	96.05
Mouth	342	323	22	19	94.44

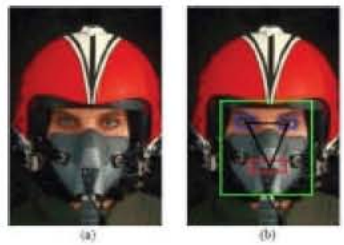


Fig. 12: (a) a sample partial occluded face, (b) localizing occluded mouth by using geometric relation between detected facial features

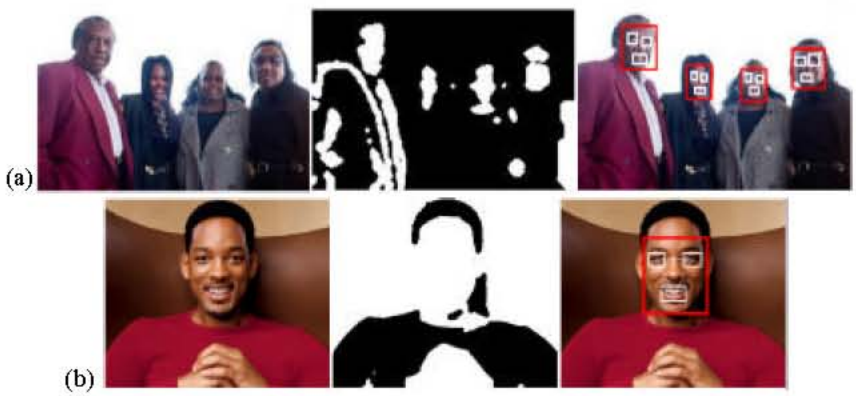


Fig. 13: Face detection examples containing dark skin pixel faces. Each example contains original image, masked skin color regions by using skin color segmentation and face and facial feature detection result after using flexible geometric model

Experimental Result: As mentioned before, we have used CVL database [21] in order to verify the accuracy of our proposed algorithm. The CVL face database includes pictures that have been taken from 114 subjects. The images are 640×480 pixels in size. All of them include just a single face. For each person there are 7 images captured with different poses and facial expressions (frontal, left profile, right profile, half-left profile, half-right profile, smiling with open and shut mouth), so CVL database includes 798 images in total and our experimental result is according to use 342 frontal images (just three frontal facial expressions available for each person). Three sample images belonging to CVL database are shown in Fig. 5(a). The achieved accuracy and false alarms of our proposed algorithm for face, lips and eyes detection are reported in Table 1. The overall performance of this algorithm for face detection on CVL database has achieved 97.66% whereas [25] had reported a 94.3% accuracy rate on whole CVL database (all poses). Also eye detection and lip detection rates of our method are 96.05% and 94.44%, respectively. Our new EyeMap shows better performance than [26] that obtained 86.06% accuracy rate on these 342 frontal faces of CVL database. Furthermore, false positive and false negative rates are two important factors to evaluate a detection system. As it can be seen in Table 1, in our method these factors also have appropriate values. The proposed algorithm was tested in Windows 7 with a Core i7, 1.66 GHz CPU with a memory of 4 MB. In terms of detection time, on average, the proposed algorithm taking 1.1 ± 0.3s for the CVL database, proved faster performance than similar methods. In addition to execute the algorithm on CVL database, we applied the procedure to detect faces in multi face images. Fig. 13 demonstrates that our algorithm can successfully detect dark skin faces. These examples contain the faces with facial expression and open mouth.

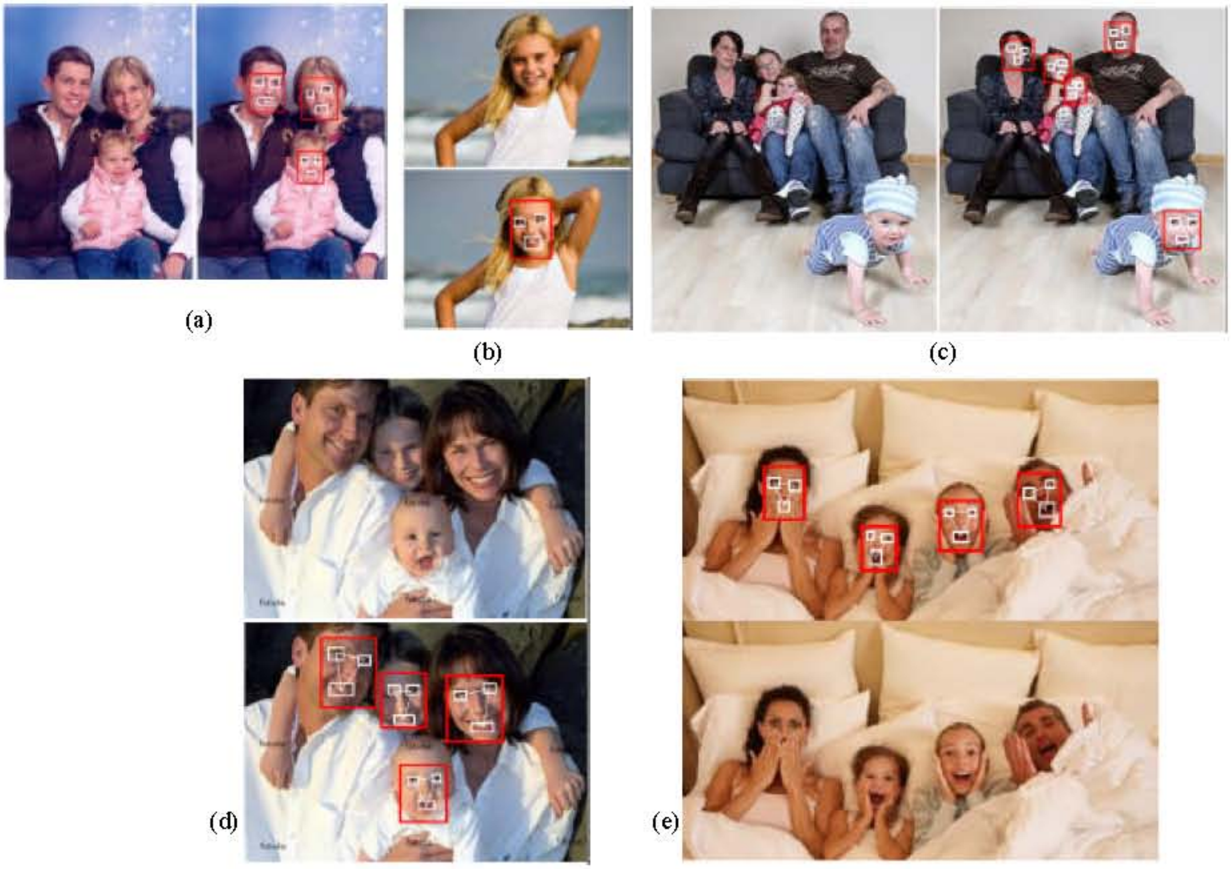
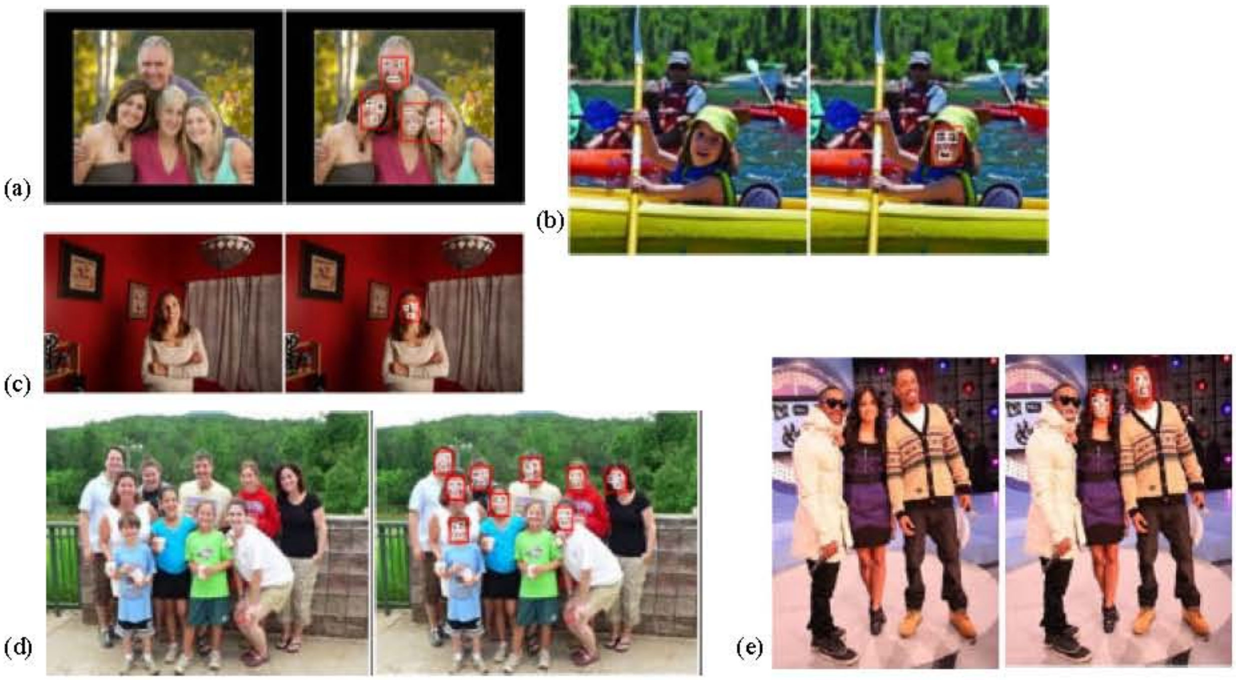


Fig. 14: Face detection result on subsets of family photos. Each images contains complex background. False negative are due to occlusion and shadows

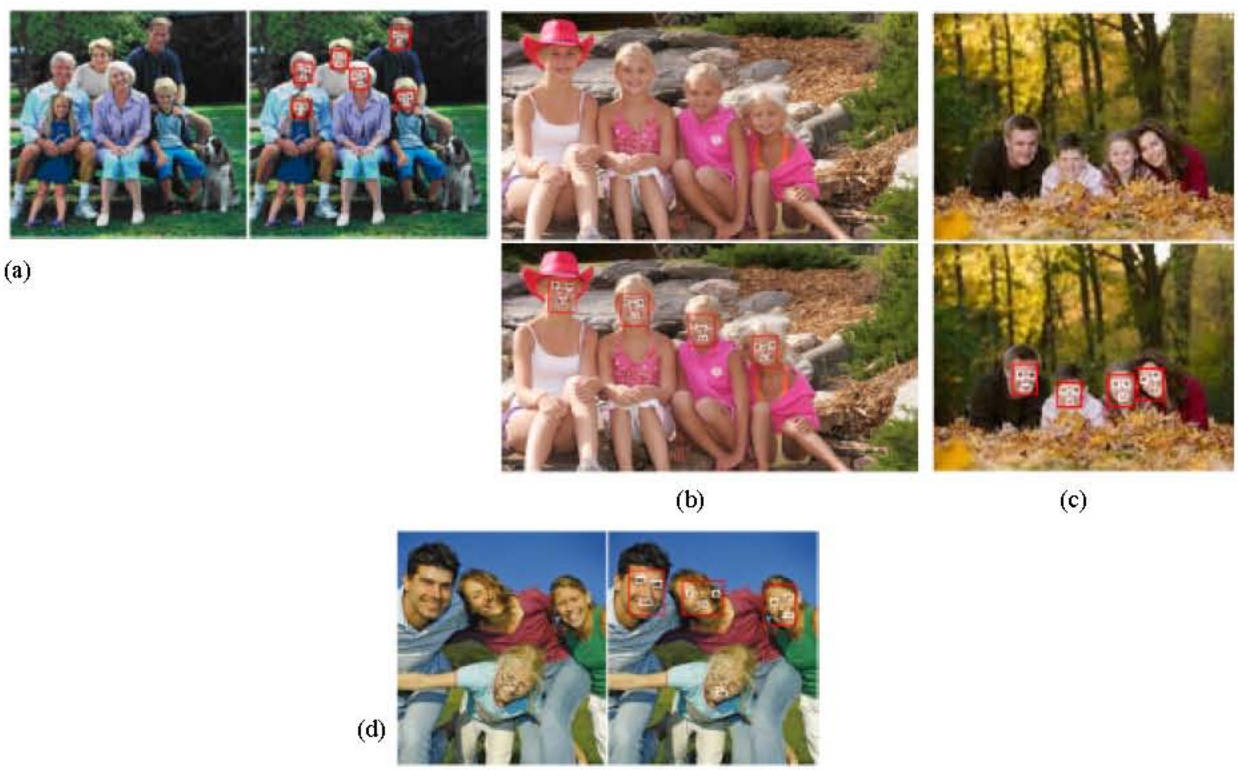
Fig. 13(a) shows result in a multi face image in spite of containing a subject who is wearing glasses. In Fig. 13(b) there is a considerable amount of extra skin color region. After localizing the facial features and making triangle structure our algorithm could find the correct face boundary. Some results on images with various conditions (facial expression, lighting variation, scale and occlusion) are shown in Fig. 14. Fig. 14(b) shows the result in an example with scale variation and partial orientation. Fig. 14(e) demonstrates the result in an image faced with facial expression and partial occlusion. This example shows that how the algorithm localizes the lost mouth by using the geometrical relation between the detected eyes. Furthermore our method is robust in dealing with various real images with more complex background. Some other results on personal collections examples with various qualities and complex background are shown in Fig. 15 and Fig. 16. These images were chosen from the internet. As expected, detecting several faces in one image is more challenging. An example of false detection is shown in Fig. 15(a). The women faces are too close together and also their hairs are blonde. So the algorithm failed to separate the face candidates. There are some other false negative examples because of occlusion (wearing glasses and sunglasses) in Fig. 15(d-e). Fig. 16(a-b) demonstrates the result on low quality and high resolution images, respectively. Fig. 16(d) shows a false negative example in face detection due to extreme lighting condition. In addition, there is a case of occlusion in woman's face because of covering an eye by the hair; meanwhile, the figure shows that how our algorithm could estimate location of the occluded eye and prevent from another false negative in face detection.

By using just skin color segmentation, some false regions are also extracted as human faces. The false alarm of algorithm is decreased after using component-based detection (lips, eyes and triangle structure). However the proposed method fails to find a face in case of detecting no components at all, but our algorithm manage to detect in the case that at least both eyes or just an eye and the mouth are detected in each face. In addition, in terms of detection time this algorithm is almost independent of the image size.



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

Fig. 15: Face detection result personal collections photos with complex background. The images have been selected from the internet. There are some false negatives due to occlusion (wearing glasses and sunglasses) and extreme lighting condition



(a) (b) (c) (d)

Fig. 16: Face detection result on some multi face examples with complex background and various image quality. The images have been selected from the internet. False alarms are due to occlusion, pose variation and extreme lighting conditions

CONCLUSION

Skin detection is an important ahead step in image filtering, which affects the precision of latter processing directly. It is important for us to probe into how to increase face detection precision. In this paper, a robust component-based face detection algorithm based on color features was presented. This paper first introduced a skin color model to segment skin pixels for different ethnic groups and races. We considered two novel models to extract eyes and mouth as facial components. To verify the skin candidates we used a flexible geometric model to construct a triangle between facial components. In this way, the proposed algorithm performs well even when an eye or the mouth is occluded and so has not detected. It means that according to geometric relation between the facial features, the algorithm is able to localize a missed or occluded facial component. Because of omitting the extra non-skin pixels from next processes, proposed algorithm has a big benefit due to its computationally reduction; so after applying component detectors on only face candidates and pursuing the process by a combination of morphological operation, a robust face detection method takes just about a second in order to detect face and facial features. The accuracy of proposed technique is better than the similar approaches.

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