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Face detection using template matching and skin-color information

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Abstract

A face-detection approach is proposed in the paper. Firstly, a luminance-conditional distribution model of skin-color information is used to detect skin pixels in color images; then, morphological operations are used to extract skin-region rectangles; finally, template matching based on a linear transformation is used to detect face in each skin-region rectangle. Experimental results on some color images from the FERET database and from the Internet are encouraging. The proposed algorithm is shown to be effective and efficient in detecting frontal faces in color images.

Keywords: Face detection; Template matching; Skin-color information; Morphological operation

1. Introduction

In the last few years, we have seen an upsurge of interest in face detection as it is a necessary first step in face-recognition systems [4,16]. Face recognition has numerous commercial and law-enforcement applications, ranging from static matching of controlled-format photographs such as passports, credit cards, driver's licenses, and mug shots to real-time matching of surveillance video images and human–computer communications [1,2,6,8,17,18]. Face detection poses a wide range of different technical challenges. It requires a wide range of knowledge from image processing and pattern recognition.

Given a single image, the goal of face detection is to segment all image regions, which contain a face regardless of its three-dimensional position, orientation, and lighting conditions. Such a problem is difficult because faces are non-rigid and have a high degree of variability in size, shape, color, and texture. Typically, the slide-window technique is used to search for faces in an image so that many existing face-detection techniques are time consuming.

In this paper, we propose a face-detection approach by using template matching and skin-color information. The idea is to segment eye-pair candidates by using skin-color information and then to detect faces by using template matching. The rest of this paper is organized as follows. In Section 2, background information is introduced. A face-detection algorithm is proposed in Section 3. In Section 4, experiments are conducted and discussed. Lastly, conclusions are given in Section 5.

2. Background review

Because face-detection techniques requires a priori information of the face, they can be effectively organized into two broad categories as follows:

- feature-based approaches and
- image-based approaches.

These approaches are distinguished by their different ways to utilize face knowledge.

2.1. Feature-based approaches

Feature-based approaches have embodied the majority of interest in face-detection research starting as early as the

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1970s. The apparent properties of the face such as skin color and face geometry are exploited. Face-detection tasks are accomplished by manipulating distances, angles, and area measurements of the visual features derived from scene. Recently, numerous methods that combine several facial features have been proposed to detect faces. A typical approach begins with the detection of skin-like regions. Next, skin-like pixels are grouped together using connected-component analysis. Finally, local features are used for verification. Predefined template and deformable template can be used to model facial features effectively.

2.2. Image-based approaches

Although some of the feature-based attempts have improved the ability to cope with the unpredictability of face appearance and environmental conditions, there is still a need for techniques that can perform in more hostile scenarios such as multiple faces with cluster-intensive backgrounds. Contrasted to the feature-based approaches, the image-based approaches can learn to recognize a face pattern from examples. This eliminates the potential of modeling error due to incomplete or inaccurate face knowledge. In general, they rely on techniques from statistical analysis and machine learning to find the relevant characteristic of face and non-face images. The learned characteristics are in the form of distribution models, or discriminant functions. Meanwhile, dimensionality reduction is usually carried out for the sake of computation efficiency. The linear-subspace approaches are the most common image-based approaches, in which image patterns are projected to a lower dimensional space and then a discriminant function is formed for classification, or a non-linear decision surface can be formed by using neural network. Recently, support-vector machines and other kernel methods have been proposed [10]. These methods implicitly project patterns to a higher dimensional space and then form a decision surface between the projected face and non-face pattern.

2.3. Problems with existing approaches

Many existing face-detection approaches are time consuming even just for the task to detect a single face in an image. Here are the main problems:

- slide-window technique is widely used but it is very time consuming,
- in order to detect faces with varying scales, input images have to be resized several times, and
- in order to detect faces with varying orientations, input images have to be rotated several times.

In our opinion, if we can determine eye-pair candidates in an image, the above problems can be avoided.

Generally speaking, it is difficult to determine all eye-pair candidates in an image with a complicated background. Fortunately, many face-recognition applications have simple or medium complicated backgrounds.

3. Face-detection algorithm

In this section, a face-detection algorithm for gray images is firstly proposed by using template matching based on a linear transformation. Then, skin-color information is used to detect faces in color images.

3.1. Eye-pair candidate [5]

In a gray image with a face, the gray values of some pixels within two eye regions usually are much lower than those of pixels around the eye regions. So, a threshold may be selected to segment eye regions.

Let I be a gray image with a resolution of $n \times n$,

$$I = \{I(x,y) | 0 \leqslant x < n, 0 \leqslant y < n\}. \tag{1}$$

For any given threshold θ, a binary image can be obtained as follows:

$$F = \{F(x,y) | 0 \leqslant x < n, 0 \leqslant y < n\}, \tag{2}$$

where

$$F(x,y) = \begin{cases} 0, & \text{if } I(x,y) < \theta, \\ 1, & \text{otherwise.} \end{cases} \tag{3}$$

For any given black pixel (x_i, y_i) with $F(x_i, y_i) = 0$ in the binary image, one black region can be obtained by region-growing algorithm

$$B_i = \{(x,y) | F(x,y) = 0, \quad \text{and} \quad (x,y) \text{ is a neighborhood of } B_i\}. \tag{4}$$

Let $R(B_i)$ be the rectangle which includes the black region B_i and $P(B_i) = (\bar{x}_i, \bar{y}_i)^{\mathrm{t}}$ be the central position of the black region B_i. Let B_θ be a set of all the k black regions, i.e.,

$$B_\theta = \{B_1, B_2, \ldots, B_k\}. \tag{5}$$

For any pair of two black regions, e.g. $\langle B_i, B_j \rangle$, it may be two eyes or not. If $\langle B_i, B_j \rangle$ is a pair of eyes, we can design some constraints according to the knowledge of eyes on face images. For example, it can be assumed that the distance between two eyes is no less than $d_{\min}$ and is no more than $d_{\max}$, i.e.,

$$C_1 : d_{\min} \leqslant \overline{P(B_i)P(B_j)} \leqslant d_{\max}. \tag{6}$$

It can also be assumed that there exist only rotations of no more than 45° in the face plane, i.e.,

$$C_2 : |x_i - x_j| > |y_i - y_j|. \tag{7}$$

According to general knowledge of faces, many more constraint conditions can be proposed. For simplicity, only the above two conditions are proposed here.

Let P_θ be a set of central positions of the black region pair, $\langle B_i, B_j \rangle$, which satisfies all the constraints

C_1 and C_2, i.e.,

$$P_\theta = \{\langle P(B_i), P(B_j)\rangle | B_i, B_j \in B_\theta, \\ C_1 \text{ and } C_2 \text{ are satisfied}\}. \tag{8}$$

Any element in the set P_θ can be regarded as an eye-pair candidate.

3.2. Normalized-face candidate

Let T be a $m \times m$ typical face template given as follows:

$$T = \{T(u,v) | 0 \leqslant u < m, 0 \leqslant v < m\}, \tag{9}$$

where the position of the left eye is $P_L = (u_L, v_L)^t$ and the position of the right eye is $P_R = (u_R, v_R)^t$ and $v_L = v_R$ is assumed.

For any eye-pair candidate $\langle P_i, P_j \rangle$, we assumed that $\langle P_i, P_j \rangle$ could be obtained by a linear transformation of $\langle P_L, P_R \rangle$:

$$\langle P_i, P_j \rangle = A \langle P_L, P_R \rangle + A_0, \tag{10}$$

where $P_i = (\bar{x}_i, \bar{y}_i)^t$, $P_j = (\bar{x}_j, \bar{y}_j)^t$, and $\bar{x}_i < \bar{x}_j$. Thus, a linear transformation can be defined from the u–v plane to the x–y plane

$$\begin{bmatrix} x \\ y \end{bmatrix} = A \begin{bmatrix} u \\ v \end{bmatrix} + A_0, \tag{11}$$

where

$$\begin{cases} A = \beta \begin{bmatrix} \cos\psi & -\sin\psi \\ \sin\psi & \cos\psi \end{bmatrix}, \\ A_0 = P_i - AP_L, \\ \psi = \arctan\left(\frac{\bar{y}_j - \bar{y}_i}{\bar{x}_j - \bar{x}_i}\right), \\ \beta = \frac{\overline{P_i P_j}}{\overline{P_L P_R}}. \end{cases} \tag{12}$$

Then, a $m \times m$ linearly normalized-face candidate image can be obtained as follows:

$$S = \{S(u,v) = I(x,y) | (x,y) \text{ is from Eqs. (11) and (12)}, \\ 0 \leqslant u, v < m\}. \tag{13}$$

Examples of the eye-pair candidates and the corresponding normalized-face candidate images can be seen in Fig. 1.

Let Ω be the set of all the normalized-face candidate images, i.e.,

$$\Omega = \{S | S \text{ is the normalized-face candidate} \\ \text{image of } (P_i, P_j) \in P_\theta\}. \tag{14}$$

Note that most of the normalized-face candidate images may not be true-face images.

3.3. Template matching

The similarity between a normalized-face candidate image S and the face-template image T can be measured as follows:

$$\rho(S,T) = \frac{1}{\sigma(S)\sigma(T)} \sum_{u=0}^{m-1} \sum_{v=0}^{m-1} \left(S(u,v) - \bar{S}\right)\left(T(u,v) - \bar{T}\right), \tag{15}$$

where $\bar{S}$, $\bar{T}$ are the means of S and T, respectively, and $\sigma(S)$, $\sigma(T)$ are the standard deviations of S and T, respectively.

The best matching, S_{opt}, can be found

$$S_{opt} = \arg \max_{S \in \Omega} \rho(S,T). \tag{16}$$

Assume that there is no more than one face (i.e., only one face or no face) in the image I. Thus, a face/non-face classification function, $FACE(\cdot)$, can be made

$$FACE(I) = \begin{cases} 1 & \text{if } \rho(S_{opt}, T) \geqslant \rho_0, \\ 0 & \text{otherwise}, \end{cases} \tag{17}$$

where ρ_0 is a similarity threshold.

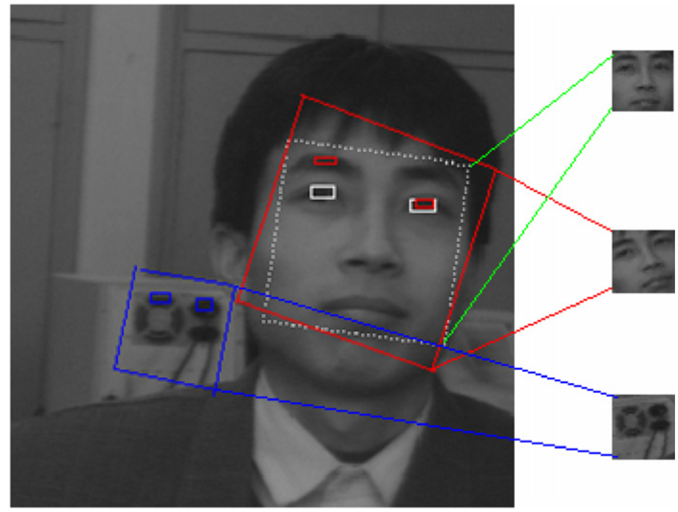

Fig. 1. Examples of the eye-pair candidates and the corresponding normalized-face candidate images.

3.4. Skin-color information

Skin color is an important apparent property for face detection. Skin color differs from race to race, and depends on the lighting conditions. Modeling skin color requires choosing an appropriate color space and identifying a cluster associated with skin color in this space. Some color models in the HSV-YCbCr space were proposed in [3,9,15]. Soriano et al. [13] discussed an adaptive skin-color model in the normalized RGB space.

Hsu et al. [4] proposed a non-linear transformed YCbCr color space and an elliptical skin model in the transformed space. The elliptical model for the skin tones in the transformed space is described in Eqs. (18) and (19).

$$\frac{(x - ec_x)^2}{a^2} + \frac{(y - ec_y)^2}{b^2} = 1, \tag{18}$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} C_b' - c_x \\ C_r' - c_y \end{bmatrix}. \tag{19}$$

From Eqs. (18) and (19), the skin tones in the transformed space are modeled by using a Gaussian distribution, where Eq. (18) is the 50% probability ellipse of the Gaussian distribution. Let

$$Z = \begin{bmatrix} C_b' \\ C_r' \end{bmatrix}. \tag{20}$$

By using the linear transformation of Eq. (19), we can reformulate the Gaussian distribution of Z in the transformed space by the mean μ in Eq. (21) and the covariance matrix Σ in Eq. (22).

$$\mu = \begin{bmatrix} 106.7 \\ 151.0 \end{bmatrix}, \tag{21}$$

$$\Sigma = \begin{bmatrix} 497.0 & -210.5 \\ -210.5 & 344.5 \end{bmatrix}. \tag{22}$$

According to probability theory, we can calculate the probability inside an ellipse:

$$P\{(Z-\mu)^{\mathrm{t}}\Sigma^{-1}(Z-\mu) \leqslant \lambda\} = 1 - \exp\left(-\frac{\lambda}{2(1-r^2)}\right) \hat{=} p, \tag{23}$$

where r is the correlation coefficient. Therefore, skin-pixel classification rule can be reformulated by using the $100p\%$ probability ellipse as follows:

$$\varphi(Z) = \begin{cases} 1 & \text{if } (Z-\mu)^{\mathrm{t}}\Sigma^{-1}(Z-\mu) \leqslant \lambda, \\ 0 & \text{otherwise,} \end{cases} \tag{24}$$

where λ is determined by the probability p in Eq. (23).

Hsu's Gaussian model can perform well in skin-pixel classification. It is also observed that the distribution of Z in the transformed space changes with the small/large luminance. The range of luminance was divided into five intervals: [0, 40], [40, 60], [60, 190], [190, 210], [210, 255] in [7]. Five skin-tone clusters corresponding to the five different luminance intervals are shown in Fig. 2.

In Fig. 2, the ellipse is the 90% probability ellipse of Hsu's Gaussian distribution. Obviously, different Gaussian distributions are needed to model the skin-color information for different luminance values. Corresponding to each luminance interval, one Gaussian distribution can be assumed, with the mean μ_k and the covariance matrix Σ_k ($k = 1, \ldots, 5$). These five Gaussian distributions can be regarded as a luminance-conditional distribution model of skin-color information [7].

Let λ_k be determined by the mean μ_k, the covariance matrix Σ_k, and the probability p value by using Eq. (23). A luminance-conditional skin-pixel classification rule can be proposed as follows:

$$\phi(Z, Y) = \begin{cases} 1 & \text{if } (Z-\mu_k)^t\Sigma_k^{-1}(Z-\mu_k) \leqslant \lambda_k, \\ 0 & \text{otherwise,} \end{cases} \tag{25}$$

where $k = k(Y) \in \{1, 2, 3, 4, 5\}$ is determined by the luminance component Y.

3.5. Detecting multiple faces

In this paper, the luminance-conditional distribution model of skin color information is utilized to detect skin pixels in color images. The skin pixels detected may form several skin regions in the color image. Usually, there are some false skin pixels detected because of noise in the color image. The binary morphological operations can be utilized to remove the false skin pixels. Then, all the skin regions can be extracted. Examples of skin regions detected are displayed in white in Figs. 3(a), 4(a) and 5(a). In each skin-region rectangle, face detection can be performed to detect a possible face.

The proposed face-detection algorithm can be summarized as follows:

- perform skin-pixel classification by using the luminance-conditional color model,
- utilize the binary morphological operations to remove the false skin pixels, to extract skin regions, and to obtain the corresponding skin-region rectangles, and
- detect face by using R-component of the input color image and using template matching in each skin-region rectangle.

It is noted that the skin-pixel information can be utilized to select the threshold θ in Eq. (3). Usually, θ can be selected to be no more than the average intensity of skin pixels.

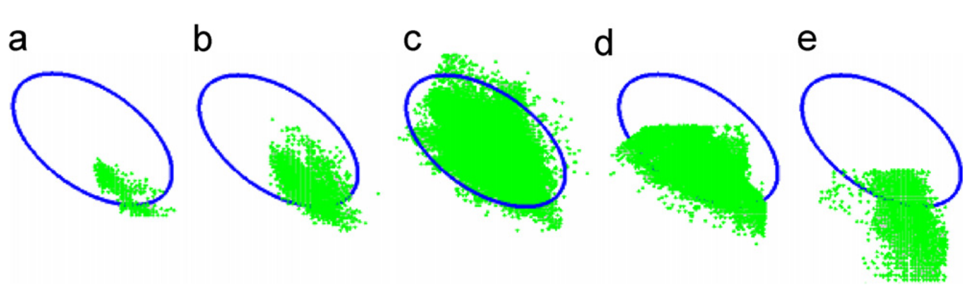

Fig. 2. The skin tone clusters shown for: (a) $Y \in [0, 40]$, (b) $Y \in (40, 60]$, (c) $Y \in (60, 190]$, (d) $Y \in (190, 210]$, and (e) $Y \in (210, 255]$.

Fig. 3. With different races: (a) skin regions and (b) face detected.

Fig. 4. Under different lighting conditions: (a) skin regions and (b) face detected.

4. Experiments and analysis

In this section, firstly some skin-pixel classification experiments have been performed to show the effectiveness of the luminance-conditional color model. Then, face-detection experiments have been performed.

4.1. Skin-pixel classification

We have downloaded 446 color images containing human faces under different lighting conditions from the Internet. More than 4.3 million skin pixels and more than 4.6 million non-skin pixels have been extracted manually. Skin-pixel classification experiments have been performed by using Garcia's model [3], Wang's model [15], Liu's model [9], Hsu's Gaussian model [4], and the luminance-conditional model [7], respectively. Experimental results of the false negative rate α, the false positive rate β, and the average false rate of α and β are listed in Table 1.

From Table 1, it is observed that Hsu's Gaussian model and the luminance-conditional model perform much better than the other three models in decreasing the average false rates although Wang's model and Liu's model perform much better than the other three models in decreasing the false positive rates. And, it is also observed that the

Fig. 5. In scenes: (a) skin regions and (b) faces detected.

Table 1
False rates of skin pixel classification using five models

Model	α	β	$(\alpha+\beta)/2$
Garcia's model	0.2937	0.2012	0.2475
Wang's model	0.4185	0.0380	0.2282
Liu's model	0.3070	0.0620	0.1845
Hsu's Gaussian ($p = 0.8$)	0.0675	0.1654	0.1165
Luminance-conditional ($p = 0.8$)	0.0657	0.1585	0.1121

luminance-conditional model performs a little bit better than Hsu's Gaussian model in decreasing the false rates.

4.2. Detecting faces

Face-detection experiments were done on some images from the FERET database [11,12] and some color images from the Internet. The proposed face-detection algorithm is shown to be effective in detecting frontal faces in color images.

Five examples with different races are displayed in Fig. 3. Five examples under different lighting conditions are displayed in Fig. 4. Experimental results on two examples of scenes with multiple faces are displayed in Fig. 5. In Figs. 3(a), 4(a) and 5(a), skin-pixel region, displayed in white, are obtained by using the luminance-conditional skin-color model and the morphological dilation operations and erosion operations. In Figs. 3(b), 4(b) and 5(b), the detected faces are displayed in the red boxes.

In experiments, the threshold θ in Eq. (3) can be effectively and efficiently selected by using the skin-pixel information. An iterative-thresholding algorithm was used to threshold gray image in [14]. The threshold range of [30, 50] was used in [9]. Due to the varying illumination conditions, the former may not be efficient while the latter may not be effective.

Experiments show that the proposed algorithm to detect faces by using template matching and skin-color information is effective and efficient in detecting frontal faces with different races and under different lighting conditions. As shown in Fig. 5, the proposed algorithm fails in detecting faces with big pose changes and fails in detecting very small faces because of the failures to segment eye-pairs.

5. Conclusions and future work

In this paper, a face-detection algorithm is proposed. The contribution of this paper is to combine template-matching technique with skin-color information in segmenting eye-pair candidates via a linear transformation and in making a face/non-face decision. Future work aims to detect some more fiducial points and to deal with pose change problems by devising nonlinear 2-D/3-D transformations.

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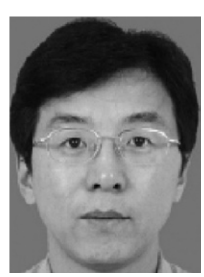

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