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Face Automatic Detection based on Elliptic Skin Model and Improved Adaboost Algorithm

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Abstract

To improve face detection rate and reduce false acceptance number with complex background, a method of face automatic detection based on improved elliptic skin extraction combining Adaboost algorithm is proposed. Firstly, the image is transformed from RGB space into nonlinear YCbCr space using nonlinear color transformation technology. Secondly, skin area is extracted based on elliptic skin model and after morphological image processing and face candidate region judgment, possible face region is determined preliminarily. Finally, face is detected accurately using improved cascade classifier. Experiments show that improved elliptic skin model can eliminate the influence of illumination and has good color extraction effects; face detection rate of proposed cascade classifier can reach 98% which is better than conventional algorithm. So the proposed method can enhance the performance and speed of face detection, and can detect face regions quickly and accurately with complex background.

Keywords: *Pattern recognition, Face detection, Color space, Skin color model, Cascade classifier*

1. Introduction

Face detection is mainly about the determination of all possible face information and space distribution such as position, posture and face number. Recently, along with the application developments of social public security, information security and e-commerce, face detection has become hotspots [1]. Face detection mainly has two methods: based on characteristics rules [2] and based on machine learning [3]. The first method analyzes the possibility of the existence of face by extracting some facial features using prior face knowledge. According to different prior knowledge, characteristic rules can be divided into facial features distribution, skin texture, facial outline and movement, etc. Although the method is simple, it is susceptible to background, illumination, face differences and it has low detection rate. The second method takes face detection as a two classification and trains classifier using a lot of face samples and non-face samples to find all possible face areas. The method mainly includes artificial neural network (ANN) [4], support vector machine (SVM) [5], and Adaboost algorithm [6]. The method needs a lot of training samples and has a long training time. Therefore, we can combine the two methods and use common advantages and avoid weaknesses to improve face detection. For examples, GUO [7] proposed a method for face detection based on skin color segmentation and improved AdaboostSVM algorithm. The method can enhance the performance and speed of face detection but it does not consider the influence of illumination and has low skin extraction efficiency with complex background. ZONG [8] proposed a face detection method which combines skin color detection and Adaboost algorithm. The new approach can detect face with better performance than skin color detection and Adaboost algorithm. But it only used original Adaboost algorithm and had a higher

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false acceptance rate.

According to the above deficiency, we propose a rapid face detection algorithm with complex background. Secondly, skin area is extracted based on elliptic skin model and after morphological image processing and face candidate region judgment, possible face region is determined preliminarily. Finally, face is detected accurately using improved cascade classifier.

2. Skin Region Extraction

We can conclude transforming image from RGB space into YCbCr space through linear transformation. Illumination is not entirely separated with chrominance. Therefore, skin extraction based on chrominance is also affected by Y component. In order to eliminate the influence, Anil K. Jain proposed a new YCbCr space based on deformation using nonlinear color transformation technology. The space is as follows:

$$\bar{Cb}(Y)=\begin{cases}108+\dfrac{(K_i-Y)\cdot(118-108)}{K_i-Y_{\min}}, if\,(Y<K_i)\\ 108+\dfrac{(Y-K_h)\cdot(118-108)}{Y_{\max}-K_h}, if\,(K_h<Y)\end{cases} \quad (1)$$

$$\bar{Cr}(Y)=\begin{cases}154+\dfrac{(K_i-Y)\cdot(154-144)}{K_i-Y_{\min}}, if\,(Y<K_i)\\ 154+\dfrac{(Y-K_h)\cdot(154-132)}{Y_{\max}-K_h}, if\,(K_h<Y)\end{cases} \quad (2)$$

$$Wc_i(Y)=\begin{cases}WLc_i+\dfrac{(Y-Y_{\min})\cdot(Wc_i-WLc_i)}{K_i-Y_{\min}}, if\,(Y<K_i)\\ WHc_i+\dfrac{(Y_{\max}-Y)\cdot(Wc_i-WHc_i)}{Y_{\max}-K_h}, if\,(K_h-Y)\end{cases} \quad (3)$$

$$C_i^{'}(Y)=\begin{cases}(C_i(Y)-\bar{C_i}(Y))\cdot\dfrac{Wc_i}{Wc_i(Y)}+\bar{C_i}(K_h), if\,(Y<K_i) or (K_h<Y)\\ C_i(Y), if\,(Y\in[K_i,K_h])\end{cases} \quad (4)$$

Where K_i, K_h are piecewise threshold value in nonlinear piecewise color transformation, $K_i=125$, $K_h=188$; $Y_{\min}, Y_{\max}$ are extreme values of Y component in skin clustering area. $Y_{\min}=16$, $Y_{\max}=235$; $Wc_i(Y)$ is width of skin area and *i* represents *b* or *r*; $Wc_b=46.97$, $WLc_b=23$, $WHc_b=14$, $Wc_r=38.76$, $WLc_r=20$, $WHc_r=10$.

Through the establishment of elliptic skin model, we can judge whether CbCr value of each pixel fells on the elliptical area. The center coordinate of skin ellipse is $(\bar{Cr},\bar{Cb})$, direction is θ, and the elliptic equation is:

$$\begin{bmatrix}x\\y\end{bmatrix}=\begin{pmatrix}\cos\theta & \sin\theta\\ -\sin\theta & \cos\theta\end{pmatrix}\begin{bmatrix}Cb-\bar{Cb}\\ Cr-\bar{Cr}\end{bmatrix} \quad (5)$$

$$\frac{(x-ec_x)^2}{a^2}+\frac{(y-ec_y)^2}{b^2}=1 \quad (6)$$

After lots of experiments on skin samples, we conclude that $\bar{Cb}=109.38$,

$\bar{Cr} = 152.02$, $\theta = 2.53$, $ec_x = 1.6$, $ec_y = 2.41$, $a = 26.39$, $b = 14.03$. So, the criterion of skin area is:

$$\frac{(x - ec_x)^2}{a^2} + \frac{(y - ec_y)^2}{b^2} < 1 \qquad (7)$$

The results of skin extraction are shown in Figure 1 (b).

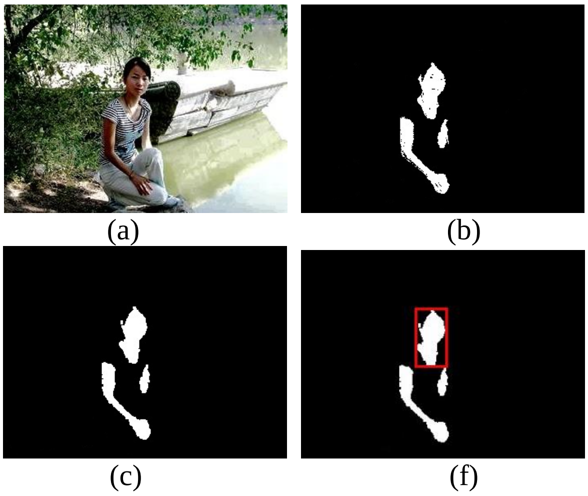


Figure 1. (a) is Original Image; (b) is the Result of Skin Extraction on Original Image; (c) is the Result Morphological Image Processing and (d) is the Face Test Result

3. Possible Face Regions Determination

3.1 Morphological Image Processing

Morphological image processing is an important research area in which the basic idea is to use certain structural elements to measure and extract the corresponding shape in order to analyze and recognize image. The main operations have open and closed operations which are based on the inflation and corrosion. We use closed and open operation to eliminate the massive and ribbon noise in binary image. The result is shown in Figure 1 (c).

3.2 Locating Possible Face Area

In order to check a skin area contains face, we use two constraints: aspect ratio and area size. A skin area that satisfies the two constraints is regarded as a possible face region. The first constraint is the ratio of the height to the width of the bounding box. The ratio is between 0.8-2.6. The second constraint is the size of bounding box surrounding the skin area. The size of possible face area is greater than 30*30. The test result is shown in Figure 1 (d).

4. Adaboost Algorithm

4.1. Haar-Like Features

Adaboost algorithm is an iterative algorithm which uses some specific Haar-Like features to train a series of weak classifier, and then extract some optimal weak classifier to combine a strong classifier. Haar-Like features proposed by Viola is a kind of simple rectangular feature. The value of a two-rectangle feature is the difference between the sums of the pixels within two rectangular regions. Viola proposed four kinds of Haar-Like features and in this paper we use five kinds of Haar-Like features, shown in Figure 2. The five kinds of Haar-Like features are orthogonal, so they can extract features completely and not produce redundancy.

Figure 2. Haar-Like Features

4.2. Cascade Classifier Improvement

The algorithm for constructing a cascade of classifiers can achieve increased detection performance while radically reducing computation time. The classifiers can be constructed which reject many of the negative sub-windows while detecting almost all positive instances. In front of each layer, the difference between negative and positive instances is obvious and the classifiers are simple with fewer rectangular features. With the increase of the layers, classifiers must gradually use more features and complex structure to distinguish the positive and negative samples. Therefore, we can conclude that the detecting process of previous classifier is more difficult than next classifier. Also we can conclude the insufficient of the algorithm that only when the samples are considered as positive, they can be detected by next classifier; otherwise rejected. There is not any remedial change for rejected positive samples. Cascade classifier along with the increase of training layers will have higher false positive rate. Experiments shows that the first classifier can refuse more than half of negative samples and the fifteenth classifier can refuse more than 90% of negative samples. To increase detection rate and reduce false positive rate, we propose a method to improve the last five classifiers.

According to original training method, the N-5th strong classifier function is:

$$f_{N-5}(x)=\sum_{t=1}^{T}\alpha^{(N-5)}h_t^{(N-5)}(x) \qquad (8)$$

Where α^{N-5} is weight coefficient; $h_t^{N-5}(x)$ is the optimal weak classifier. So, the N-4th strong classifier function can be described as:

$$f_{N-4}(x)=\gamma_{N-5}f_{N-5}(x)+\sum_{t=1}^{T}\alpha^{(N-4)}h_t^{N-4}(x) \quad (9)$$

Where γ_{N-5} is inheritance factor. If the discard rate of negative sample is higher, γ_{N-5} is lower. For the positive samples keeping unchanged almost between two adjacent classifiers, γ_{N-5} is described as:

$$\gamma_{N-5}=0.5(r_{N-5}+1) \qquad (10)$$

Where r_{N-5} is false positive rate of the *N*-5th strong classifier detecting the negative samples (not containing previous rejected negative samples).

4.3. Algorithm Steps

The process of training the *N-4*th strong classifier is

Step 1 Given samples $(x_1,y_1),(x_2,y_2)\cdots(x_n,y_n)$ where $y_i=0,1$ for negative and positive samples respectively.

Step 2 Initialize weights, $D_t(i)=1/2l$ for positive samples; $D_t(i)=1/2m$ for negative samples. Where l and m are the number of positive and negative samples respectively.

Step 3 For $t=1,2,\cdots T$

1. Normalize the weights,

$$q_t(i) = D_t(i) / \sum_{i=1}^{n} D_t(i)$$

2. For each feature *j*, train a classifier h_j

$$h_j = \begin{cases} 1 & if \;\; pf_j < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$$, θ_j is a threshold and p_j is a parity.

The error ε_j is evaluated with respect to $D(t)$, $\varepsilon_j = \sum q_i \left| h_j(x_i) - y_i \right|$.

3. Choose the classifier h_t with the lowest error ε_t.

4. Update the weights: $D_{t+1}(i) = D_t(i) \beta_t^{1-e_i}$

Where $\beta_t = \varepsilon_t / 1 - \varepsilon_t$ and $e_i = 0$ if sample is classified correctly; otherwise $e_i = 1$.

Step 4 the *N-4*th strong classifier function is

$$f_{N-4}(x) = \gamma_{N-5} f_{N-5}(x) + \sum_{t=1}^{T} \alpha^{(N-4)} h_t^{N-4}(x)$$

the *N-4*th strong classifier is

$$H_{N-4}(x) = \begin{cases} 1 & f_{N-4}(x) \geq \theta_{N-4} \\ 0 & \text{others} \end{cases}$$

Where $\theta_{N-4} = \min(f_{N-4}(x^i))(i = 1, \cdots, m)$

Step 5 To detect the samples of the *N-4*th strong classifier rejected again, we increase a decision function

$$f'_{N-4}(x) = \sum_{t=1}^{T} \alpha^{(N-4)} h_t^{N-4}(x) + (1 - \alpha^{(N-4)}) \cdot \mu^{\zeta}$$

Where μ is decision factor and ζ is the number rejected by previous classifiers.

The decision classifier is

$$H'_{N-4}(x) = \begin{cases} 1 & f'_{N-4}(x) \geq \theta_{N-4} \\ 0 & \text{others} \end{cases}$$

5. Algorithm of Face Detection based on Elliptic Skin Model and Adaboost

The algorithm flow chart is shown in Figure 3.

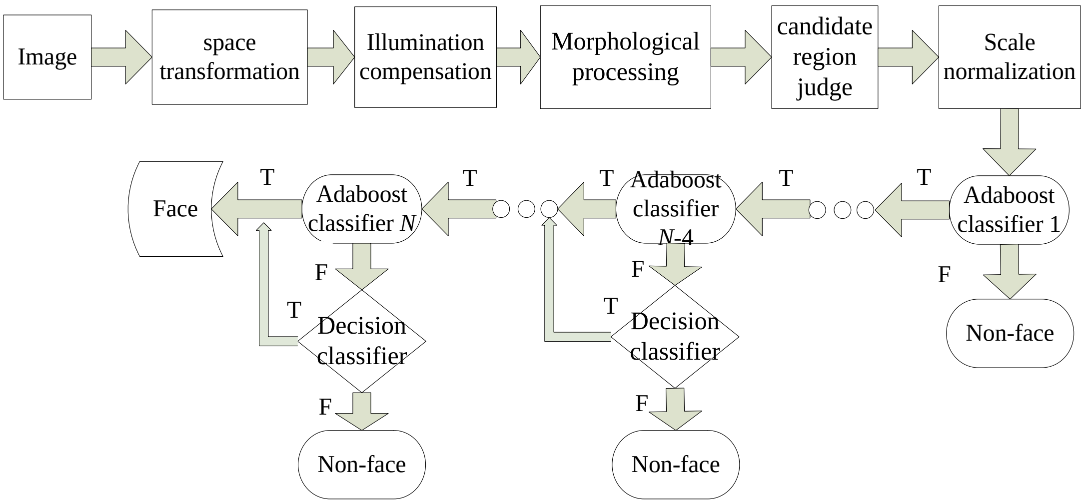
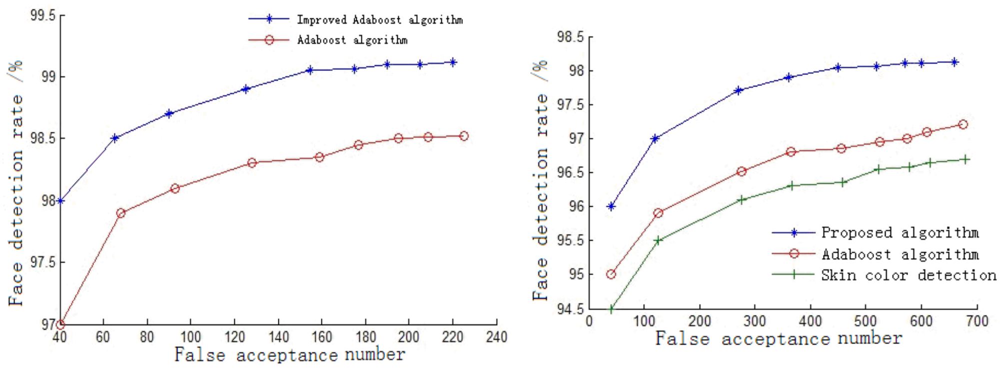


Figure 3. Flow Chart of Proposed Algorithm

6. Experiment Results and Analysis

6.1. Improved Adaboost Algorithm Performance Examination

To examine improved Adaboost algorithm performance, we test experiments on MIT-CBCL database which contains 2429 faces and 4548 non-faces. Each sample has 6279 Haar-Like features. In the paper, we require a detection rate of 100% and a maximum false positive rate of 50% for each classifier. The ROC curves of face detection are shown in Figure 4. From the curves, we can conclude that when they have the same number of false non-faces detection, improved algorithm has higher face detection rate; when face detection rate is equal, improved algorithm has fewer false non-faces detection. Therefore, the proposed algorithm has better detection performance.



(a) (b)

Figure 4. The ROC Curves of Face Detection on MIT-CBCL Database are Shown in (a); the ROC Curves of Three Methods are Shown in (b).

6.2. Proposed Algorithm for Face Detection

Experiments are performed to verify the effectiveness of the proposed algorithm. We choose 638 images with complex background and different illumination. The images totally have 1356 faces. Experimental platform is Windows XP, processor P4 2.6GHz, MatlabR2011b. The part results of face detection are shown in Figure 5. Results demonstrate the proposed algorithm can successfully detect human face in different scales, various poses, illumination conditions and complex background. In Figure 5 (d), although background is similar to skin color, side-face can be successfully detected.

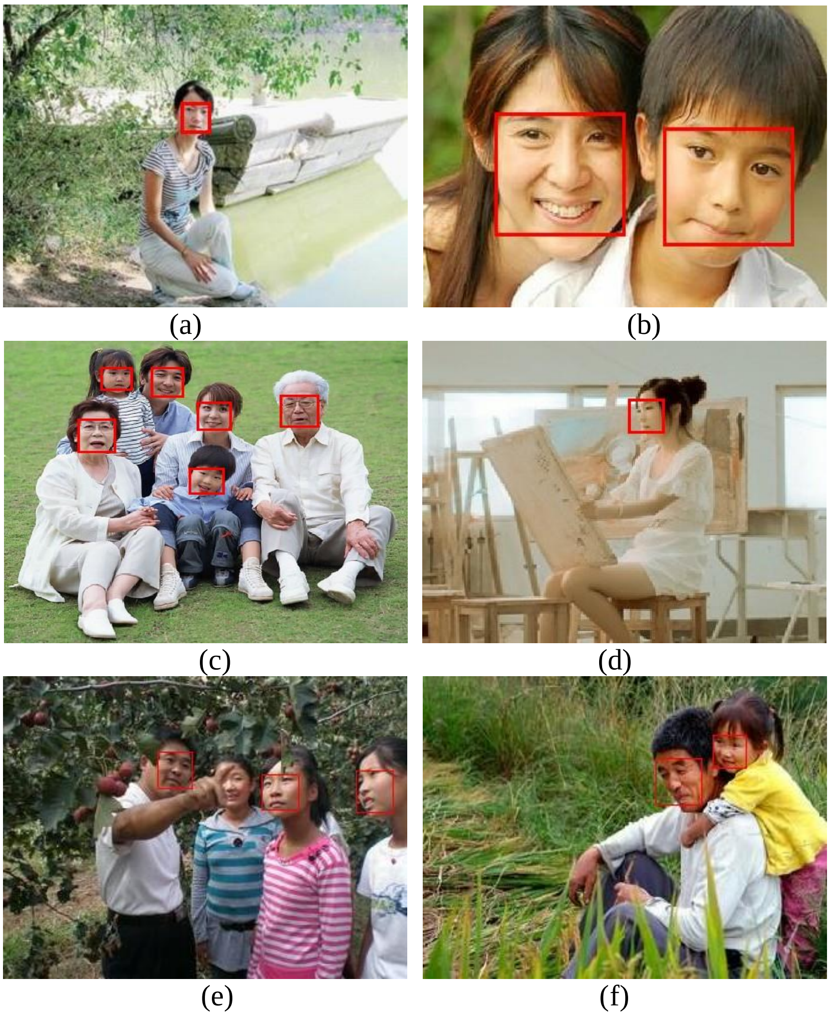


Figure 5. Some More Experimental Results

Compared with other algorithm, we respectively use Adaboost algorithm, skin color detection and the proposed algorithm to detect face. The ROC curves of three methods are shown in Figure 5 (b). Curves show that proposed algorithm is better than other algorithm in face detection rate and false acceptance rate.

The proposed algorithm not only can improve face detection, but also can reduce computational time. In Table 1 the results of execution time evaluations are presented. The average detection time of the proposed algorithm is 0.43s, face detection rate can reach 99% and false acceptance is the least.

Table 1. Computational Time

Algorithm	Face detection rate/%	false acceptance number	Time/s
Skin color detection	95.6	607	0.89
Adaboost algorithm	97.1	586	1.02
Proposed algorithm	99	289	0.43

7. Conclusions

In the paper we have presented an approach for face detection which integrates improved Adaboost algorithm and elliptic skin model. Experimental results show that the approach results in better performance than other conventional method, in terms of higher face detection rate and lower false positive rate of coping with the problems of different scales, various poses, illumination conditions and complex background.

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