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Algorithm for Face Detection Combining Geometry Constraints and Face-Mask

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Abstract: As different backgrounds can make the different views of the human faces, the traditional face detection algorithms perform not very well when the faces are pose-varied and small. This study presents a new face detection algorithm for color images which have the complex background. The proposed method combines geometry constraints and face-mask. The candidate faces can be detected by the geometry constraints between face and hair. The method based on the face-mask is employed to improve the detection accuracy. The experimental results on three datasets in the study show that the proposed method is feasible and effective.

Key words: Gauss-skin mode, adaptive light compensation, morphological denoising, face-mask

INTRODUCTION

Generally, Face detection can be described that whether there are faces in static or dynamic images. If there are faces in these images, all faces should be divided from the background and the position and size of each face should be made sure (Majumder *et al*., 2011). Face detection first used in the face recognition field. However, with the application background of face recognition is gradually complicated, face detection is paying more and more attention in the world and used in more and more widely field. As an independent research subject, the requirements of the algorithm for face detection are more and more rigorous.

Because the face is no-rigid and pose-varied, it is easily influenced by many factors, such as background, illumination and so on, which increase the difficulty of face detection. There are many face detection methods, which have their own advantage and deficiency. At present, the domestic and foreign scholars put forward many effective face detection algorithms. According to the color type of the image, these are divided into two kinds: the skin color approaches and the gray information approaches. The Skin Color Approaches (SCA) (Yang *et al*., 2002) are fast and not sensitive to multi-attitude, but they are difficult to determine whether non-face regions that have the skin-like color are face regions. So the false detection rate is quite high. The gray information approaches have strong robustness, including template matching methods (Chen and Guo, 2006) and statistical classification methods based on artificial neural network (Liu *et al*., 2006) or Support Vector Machine (SVM) (Hsu *et al*., 2002).But these methods have large calculation and need to collect a large number of training samples. So they are slower than the skin color approaches. Guo proposed an enhanced cascade structured Real AdaBoost algorithm by inheriting historical knowledge partly (AdaBoost) (Guo, 2007) for a better detection accuracy in 2007. Noticing the problem of time consuming, in 2009, Xiaoming proposed a face detection algorithm based on geometry constraints between face and hair (GC) (Gu *et al*., 2009). Aim at the high detection error r ate of GC, Lijie proposed a HAD-adaboost algorithm for face detection in color images (HAD-AdaBoost) (Lijie and Zhengming, 2012) in 2012.Compared with GC, HAD-AdaBoost has a higher detection accuracy and a lower detection error rate. However, time consuming remains a major challenge for HAD-AdaBoost training.

This study puts forward the face detection algorithm combining the geometry constraints and face-mask (GCFM). The first stage of GCFM is the face detection based on geometry constraints for location the candidate face regions. The second stage of GCFM is the face detection based on face-mask, which removes many non-face regions. GCFM can greatly reduce the influence of the complicated background. Especially, the error rate of the algorithm is much smaller than GC. At the same time, the study present the image processing method of the adaptive light compensation, which improve the effect of color clustering, solve the influence of the illumination and further improve the accuracy of the face detection. In addition, Compared with HAD-AdaBoost, GCFM has lower time consuming because of the non-training time of GCFM.

FACE DETECTION BASED ON GEOMETRY CONSTRAINTS

Adaptive light compensation: As known to all, the skin-color and hair-color are easily influenced by the illumination, the image background and the color

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deviation of the image acquisition devices (for example, the color is slant cold or slant warm and the picture is slant yellow or slant green). In view of the situation, the algorithm of the adaptive light compensation (Xiaohui and Zhisheng, 2006) is proposed. The algorithm can greatly reduce the color deviation and make the skin-color regions and the hair-color regions effectively segment. The specific steps are shown as follows:

- Transform the image from the RGB color space to the YCrCb color space, then compute the luminance value Y of each pixel in the image
- Let the luminance value Y in descending order and take the top 5 percent of the sorted pixels as set A1.Then Let E be the minimum luminance value of set A1 and make the luminance value of set A1 be 255. Meanwhile, make the value R, value G and value B of set A1 in the original image be 255. In the same way, take the bottom 5 percent of the sorted pixels as set A2 and let B be the maximum luminance value of set A2. Then make the luminance value of set A2 in the original image be 0 and the value R, value G, value B of set A2 be 0
- Take the middle 90 percent of the sorted pixels as set A3. In the meantime, according to the formula (1), adjust the value R, value G, value B of set A3:

$$g(x,y)=255*(\ln f(x,y)-\ln B)(\ln E-\ln B) \tag{1}$$

Among them in the formula (1), f (x, y) means the value of the input image and g (x, y) means the value of the output image. Figure 1 shows the comparison of images after adaptive light compensation. Clearly, Fig. 1 (a) and Fig. 1 (b), respectively show the original image and the image after adaptive light compensation.

Fig. 1(a-b): The comparison of images after adaptive light compensation, (a) The original image and (b) The image after adaptive light compensation

Skin color segmentation based on Gauss-skin model: Color of skin is the important information of the face and hard to be influenced by the changes of poses. So the face region can be quickly located by the skin-color (Hu *et al*., 2011). At present, the color space mostly contains RGB, YUV, HIS and YCrCb, especially, the RGB and YCrCb are the most widely used. Due to the three primary components of the RGB color space all contained brightness information, which is greatly influenced by the illumination. The YCrCb color space includes the Y component, Cr component and Cb component. But the Cr component and Cb component are the luminance component and do not contain brightness information. The YCrCb color space has the characteristic of luminance and chrominance separation. Hence, in the study, the skin-color regions can be segmented in the YCrCb color space. Obviously, the images got from the digital camera are the RGB images. So the study converts the RGB images to the YCrCb images. The formula which converts the RGB color space to the YCrCb space is shown in the formula:

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.2990 & 0.5870 & 0.1440 \\ -0.1687 & -0.3313 & 0.5000 \\ 0.5000 & -0.4187 & -0.0813 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 0 \\ 128 \\ 128 \end{bmatrix} \tag{2}$$

Then the skin-color model is established in the YCrCb color space. In the study, the method base on the Gauss-skin model under the YCrCb color space is proposed (Cui and Ran, 2009). The method mainly uses the normal distribution in order to fit the probability density distribution of the skin-color. The specific process is shown in the formula and formula:

$$p(C_b,C_r)=\frac{\exp\left[-0.5(x-m)^T C^{-1}(x-m)\right]}{2\pi\bullet|C|^{\frac{1}{2}}} \tag{3}$$

$$m=E(x), x=(C_b,C_r)^T \quad C=E\left[(x-m)(x-m)^T\right] \tag{4}$$

Among them in the formula (3) and formula (4), Let Cb and Cr be the two chrominance components in YCrCb color space. P (Cb, Cr) means the probability that each pixel is the skin-color pixel. Let m and C be the mean and the covariance, respectively.

According to the statistical results, the value of m and C in the Gauss-skin model can be got, which is shown in the formula and formula:

$$m = [151.2936 \;\; 114.3072] \tag{5}$$

$$C = \begin{bmatrix} 235.0891 & 9.0332 \\ 9.0332 & 132.6054 \end{bmatrix} \tag{6}$$

Let I = p (Cb, Cr) * 255 be the gray value. Obviously, the larger the value p (Cb, Cr), the larger the value I. Therefore, if only a threshold is determined to divide I into 0 and 255, the binary image which can separate the skin-color region and the other region can be got. Here, the threshold is 186.

Hair color segmentation based on illumination compensation: As is well-known, the image brightness is increased after the illumination compensation and the hair-color regions are relatively concentrated (Pouya *et al*., 2012). The experimental results show that it is enough to distinguish between the hair-color regions and the other regions in the certain threshold range of the gray value. Therefore, The process converting the color image to the YCrCb color space is not necessary.

Morphological denoising: Because of the influence of the complex background, there are some isolated noises in the image. In view of the situation, the morphological operation based on OpenCV for denoising is presented (Bradski and Kaehler, 2008).The morphological operation mainly contains the erosion operation and the dilation operation. The erosion operation can eliminate the boundary points of the image area. In addition, the erosion operation can effectively remove not only the isolated noises in the face image background and the unsmooth bulges of the face boundaries but also the small connected regions. The dilation operation can fill the holes in the image to generate the connected regions and level up the unsmooth sags of the face boundaries.

Face coarse location: Face is not the rigid object, so the face can not be simply located through its shape. But in the processing of the human face detection, it is not hard to find that the geometry constraints between the face and the hair (Zhu and Zhang, 2012). If there is a man's face to appear, the top of the face must be the man's hair

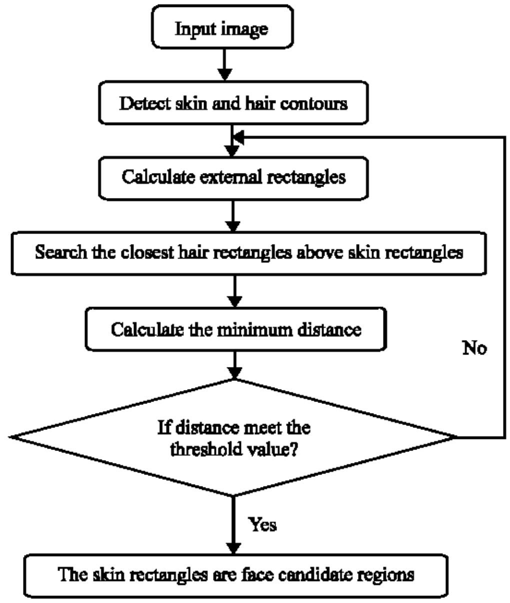

Fig. 2: The flow chart of face coarse location

and the distance between the face and the hair must be the minimum. Based on the prior knowledge, in the study, the face detection method based on the geometry constraints between the face and the hair is proposed. The specific process is shown in Fig. 2. According to the method, the candidate face regions can be easily got.

FACE DETECTION BASED ON FACE MASK

Actually, the images may have many big skin-color regions, such as the hands, feet, neck and background. So the candidate face regions exist many non-face regions. In the study, an improved face detection method base on face-mask (Zhong and Feng, 2012) is proposed to remove these non-face regions. The processes of this method are as follows: (assume each candidate region only has one face).

- Let 2d be the minimum detected face scale (d = 10). For each candidate region (width = 2d and height = 2d), define (i j) (i<width and j>height) be the coordinate of each pixel in the region. Get the window of 2d which takes the pixel at the center. Meanwhile, Let the face-mask image shown in Fig. 3 be the same scale
- Let the window and the face-mask overlap. Calculate the number of skin-color pixels belong to the circle of the face-mask image. Let center rate (rc) be the rate of the calculated numbers and the area of the circle. Similarity, let square rate (rs) be the rate of the

Fig. 3: The face-mask image

number of skin-color pixels belong to the four corner regions of the face-mask image and the area of four corner regions. If *rc* and *rs* are all satisfied the threshold value range (in this study, rc = 0. 87 and rs = 0. 38), continue to the next step. Otherwise, tack back to the step (1) and detect the next pixel

- For the face is ellipse-like and below the face and neck, it is needed to calculate the horizontal integral(fh) and vertical integral(fv) of the window. If it is satisfied the condition (fv (2d)>d, fv (d)> 1.5d, fh (d)>1.5 d), enlarge the scale of face-mask d = d*1.2 and turn back to step (2). Otherwise, continue to the next step
- If d satisfy the condition (d = 10 and 2d = min (width, height), the window has a face. Let (rc-rs) be the similarity of existing face and 2d be the scale of the face. Loop end. Then detect the next candidate region. Otherwise, tack back to the step (1) and detect the next pixel

EXPERIMENTS and RESULTS ANALYSIS

Experiments on test set: the MIT+CBCL dataset and the MIT+CMU dataset: The MIT+CBCL dataset and the MIT+CMU dataset are used as the test set. The experiments are conducted on the software MATLAB R2010a. The MIT+CLCB dataset contains 2429 face samples and 4548 non-face samples with resolution of 19×19. The MIT+CMU test set composed of 125 images containing 481 faces with resolution of 20×20. To demonstrate the effectiveness of GCFM, three methods are tested on all the samples in the MIT+CBCL dataset ant the MIT+CMU dataset. The three methods are GC, HAD-AdaBoost and GCFM. A ROC curve by simulation experiment in the MIT+CBCL dataset and the MIT+CMU dataset is shown in Fig. 4 and 5, respectively. The vertical ordinate indicates the face Detection Rate (DR) and each layer is 0.01. The horizontal ordinate indicates the False Positive Rate (FPR) and each layer is 0.05. According to Fig. 4, the DR of GCFM is 0.961 and the FPR is 0.042, while the DR of GC and HAD-AdaBoost are 0.913 and 0.959 and FPR are 0.046 and 0.043, respectively. Obviously, GCFM is more effective. As shown in Fig. 5, when the FPR is 0.1, the DR of GCFM is 0.895, while the DR of HAD-Ada Boost is 0.890 and the DR of GC is 0.879, which means GCFM possesses high DR in the same FPR.

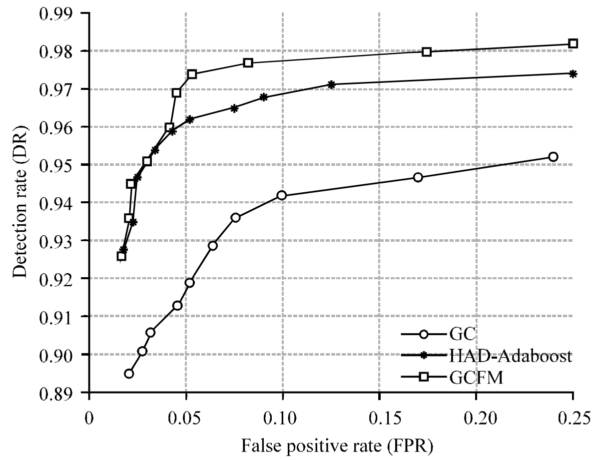

Fig. 4: ROC curve of three algorithms for face detection on the MIT+CBCL dataset

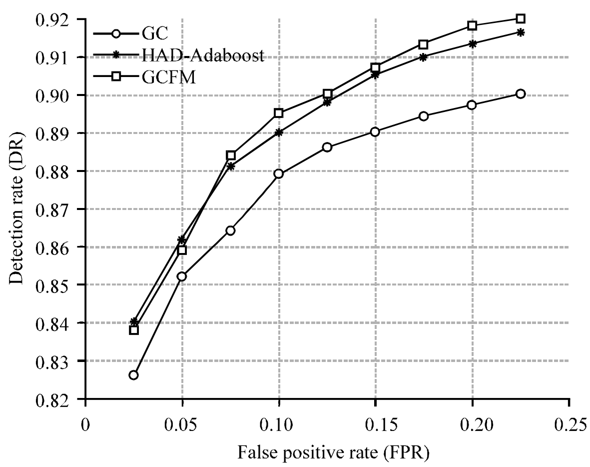

Fig. 5: ROC curve of three algorithms for face detection on the MIT+CMU dataset

Experiments on test set: The color image set: The experiment is accomplished in the Visual Studio 2008 platform based on OpenCV. The images are all from the network and digital cameras. There are 100 pictures including 846 faces in our test set. These images have the complex background, uniform illumination and low brightness, which include many clear faces and no clear faces with different attitudes. The performance comparison of GC, HAD-AdaBoost and GCFM on the color image set are shown in Table 1.

Fig. 6(a-c): Comparison of face detection between GC and GCFM, (a) A pair of original images, (b) Detection results by GC and (c) Detection results by GCFM

Table 1: The performance comparison of GC, HAD-AdaBoost and GCFM on the color image set

Method	Right number	False number	DR (%)	FPR (%)	Time (s) average
GC	771	39	91.3	4.6	0.323
HAD-AdaBoost	782	15	92.6	1.7	2.963
GCFM	785	16	92.8	1.8	0.645

As shown in Table 1, the DR of GCFM is 92.8 and the DR of GC is 91.3. The FPR of GCFM is 1.8 and the FPR of GC is 4.6. The results show GCFM is superior to GC with higher DR and extremely lower FPR. Because GCFM not only takes advantage of GC, but also uses the improved face detection algorithm based on the face-mask. This greatly reduces the interference of the skin-like color noises and hair-like color noises, which effectively reduces the error rate. GCFM is also superior to the HAD-AdaBoost. Compared with the HAD-AdaBoost, the FPR of GCFM is 0.1 higher than HAD-Ada Boost. However, the average time of HAD-AdaBoost is 2.963 and the average time used by GCFM is 0.645, which shows that the time complexity of GCFM is much smaller than HAD-Ada Boost. Because HAD-AdaBoost needs a large number of training samples to extract face features which spends a lot of time, but GCFM does not need. In order to specifically demonstrate the effectiveness of GCFM, two detail examples of the experiments are shown in Fig. 6a, shows the pair of original images and the background of these images are all complicated. From left to right, the right number of faces in these two images are 19 and 22. As shown in Fig. 6b, GC detects 30 faces and 37 faces, while 13 false faces and 14 false faces are detected, respectively. Although GC can detect almost all face regions, the result regions also contain arms, legs and clothes whose color are similar to skin (Fernandez *et al*., 2012). Therefore, the FPR of this method is quiet high. However, in Fig. 6 c, GCFM detects 17 faces and 21 faces, while 2 faces and 1 face are missed, respectively. GCFM which takes the improved method based on face-mask into account makes a more precise face location and much lower FPR.

CONCLUSION AND FUTURE WORKS

This study puts forward a face detection algorithm combining the geometry constraints between the face and the hair and face-mask. Because of the adaptive light compensation for the low-light image, the ideal region segmentation can be achieved. Compared with the traditional algorithm, this algorithm does not need to collect the training sample and extract face features. The method also adapts to the face detection for the fuzzy and small target. Meanwhile, combined with the face detection algorithm based on the face-mask, it has better detection results for the images which have many kinds of the skin-like color noises and hair-like color noises in the complicated background. However, when the face exists many occlusion and overlap, the missed rate is quite high. Moreover, when the face rotation angle is large, the face detection results are not satisfied. In the above situation, on the one hand, the video sequence image detection method is considered. That's to say, the human face can be detected by the algorithm based on the moving target tracking. On the other hand, it can be divided face-mask into many kinds, such as the frontal face-mask, side face-mask and so on.

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