Face and Eye Location of Multi-pose under Illumination

Shuze Geng1,2 Jing Luo 1,2

1 Key Laboratory of Advanced Electrical Engineering and Energy Technology, 300387, China
2 College of Electrical Engineering and Automation, Tianjin Polytechnic University, Tianjin 300387, China

Corresponding author is Shuze Geng

Abstract
Active shape model (ASM) is one of the algorithm, which is widely used in object area location so far. However, the effect on detecting face in non-uniform illumination and multi-pose face image is not satisfied. In order to improve the accuracy of locating the face and eyes through ASM algorithm under non-uniform illumination, the paper puts forward the method of combining Gabor features in the direction of gradient mean and local ASM model, which can upgrade the robustness under the condition of non-uniform illumination. The experiment shows that compared with the standard ASM algorithm, this improved method can rise location monitoring of face and eyes by 11.79% and 18.35% respectively.
Keywords: ASM, FACE DETECTION, GABOR, EYE LOCATION, INTEGRAL PROJECTION

1. Introduction

Generally speaking, eye location studies [17-18] [22] [24] [27-28] mainly on how to obtain the coordinate of eyes in given images quickly and accurately. It can be said that eye location is a hot research issue in the field of machine vision and image processing, such as face calibration, man-machine exchange, eye movement direction and so on. Meanwhile, it is one of the key technology in the research direction of fatigue monitoring of drivers, line of sight tracking, eye mouse and so on. Till now, mature algorithm of eye location includes near infrared illumination method [2-3] [11] [13], geometrical features of eyes, texture features and some other methods [1] [4-5] [9]. Near infrared illumination method depends on the characteristics of differences, which refers to the differences between the reflection of eyes to the near infrared light and other areas in the face to locate eyes. However, this kind of method does not achieve ideal effect in location outdoors in day due to the influence of the solar radiation. For example, Bogusław Cyganek and some others [3] set eye feature model on the basis of the property eye to the infrared spectrum, and then achieve eye location through cascade classifier. In addition, Cameron Whitelam and others [2] works on the short wave infrared spectrum in the five different frequency band

(1150nm~1550nm), and imply 2D normalization. As the wave gets the wavelength combination of the eye in frequency band, then the accurate coordinate of the eye is reached. Boguslaw Cyganek, Slawornir Gruszczynski [13] put forward a system for driver's eye recognition from near infrared images . This system contains two classification modules. The frist one is based on a novel eye model suited for the near infrared images, which is mainly used for eye detection. The second one is based on the higher-order decomposition of a tensor with geometrically deformed prototypes, which is responsible for eye validation. Basing on geometry , gray, texture features means to make use of them to build parameter feature model. Classifier is obtained through the process of training, classification learning and then the classifier locates the eye. Though this kind of method has a good detecting effect, it needs a large number of samples and features when building the parameter model. That is why the computational quantity is complicated. For instance, Stefano Berretti and other partners [4] extract the scan 3D keypoints and then measure how the face surface changes in the keypoints neighborhood using local shape descriptors. At last the face similarity is evaluated by comparing local shape descriptors across inlier pairs of matching keypoints between probe and gallery scans. Roberto Valenti, Nicu Sebe [9] and others put forward combined visual gaze estimation system according to the posture of the head and the position of the eye, which increases the robustness of eye location in intricate posture.

In addition many other experts also use ASM [16] [21] [26] algorithm to detect and identify face [19-20] [23] [25] and eye [6-8] [12] [15]. For example, Ying Li [6] propose a multi-template ASM algorithm addressing facial feature points detection under non-linear shape variation of facial images with various kinds of expression. By adding texture information, adopting asymmetric sampling strategy for the feature points on outer contour of face, building multiple templates and integrating local ASM and global ASM, experimental results show that the multi-template ASM algorithm outperforms traditional single template ASM. Carlos A. R. Behaine and other partners [12] put forward a new ASM mark feature point model of increasing the face feature weight and adjusting information mutually, which not only improves the stability of the face feature, but also makes the effect of detection more robust. Federico M. Sukno with others [7] build nonlinear strength model on the basis of ASM in which the differential invariant property serves as the local image descriptor to analyze the effect of face identification. Zhangbo, Wang Wenjun and others [15] put forword the theory of using alternately the local ASM and global ASM with the purpose of strengthening the pose adaptability of ASM algorithm and locating the eye area by average synthesis precise filter algorithm. Because ASM uses the method of local topological constraint, so the detection effect is relatively good. However, its pose adaptability is poor and easily influenced by the illumination effect.

Figure 1 shows the face detecting result under non-uniform illumination by traditional ASM algorithm. The pictures show that the detecting effect is not ideal.

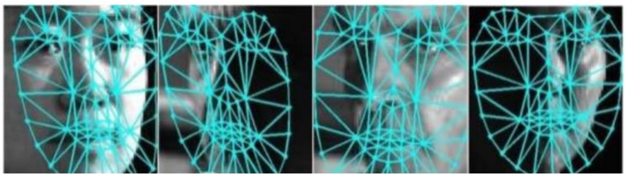


Figure 1 The face detecting result undernon-uniform illumination by traditional ASM algorithm

In order to improve the accuracy of locating the face and eyes through ASM algorithm under non-uniform illumination, the paper puts forward the method of combining Gabor features in the direction of gradient mean and local ASM model to detect face. Also, at the face region, the other method of connecting local ASM eyes template and integral projection technique is used to realize dual position of eyes. On the basis of the results of the two kinds of methods, the paper puts forward adjusting their result weight by variance function and finally figure out the position of eyes according to weight parameter, which enhances the accuracy rate of eye location.

2. Establishment of ASM model

ASM algorithm was put forward by Cootes and his partners in 1995 [14], which is widely used in object area location presently. It is a kind of deformable model based on point distribution, which uses a set of feature points to describe the target form. One advantage is that it cannot only adapt to the changes of form within a range, but also keep the form features of the original target, which can well avoid the influence of differences in target local area. The algorithm is divided into two sub models: global shape model and local texture model. The alternating use of the two in the process of detection makes the output of the model converge to a stable shape.

2.1. Establishment of ASM face global model

Global ASM shape model is founded on marking facial feature image manually to do some principle component analysis (PCA). It includes three steps on the whole: 1. Marking face feature points manually; 2. Shape normalization; 3.Principle componentanalysis transform.

Figure 2 gives 68 face feature points marked manually. The shape vector, which is made up of K number of feature points marked manually in a training sample, can be set like:

$$X_i = \{(x_1^i, y_1^i), \ldots, (x_{k-1}^i, y_{k-1}^i), (x_k^i, y_k^i)\}, i = 1, 2, \ldots, n \tag{1}$$

The (x_j^i , y_j^i) represents the coordinate of the j feature point in the i image, n stands for the number of the training sample. n sets of training samples consist of n number of shape vectors.

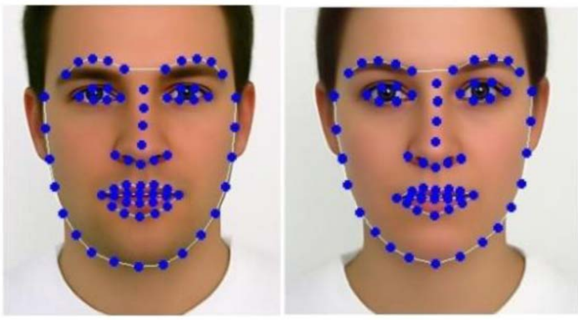


Figure 2. 68 face feature points marked manually

2.2. Shape normalization

As the n number of shape vectors are derived from n sets of face samples in different pose, so as to make the feature of shape vectors meaningful these n number of shape vectors needs to be translated, rotated and scaling transformation appropriately and then alignmented to the same point sample model on the condition that the points distribution model is not changed. This operation alignments the figure of the points distribution and makes the form more regular.

2.3. PCA transform

After the training samples are calibrated and normalized, they will experience PCA process. Steps in details are as follows:

a) From formula 1, the shape vector mean value is:

$$\overline{X} = \frac{1}{n} = \sum_{i=1}^{n} x_i \tag{2}$$

b) The vector covariance is:

$$S = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^T\left(X_i - \overline{X}\right) \tag{3}$$

c) Figure out the feature value of the covariance S and feature vector, then the feature value is specialized in order from big to small.

$$Sq_k = \alpha_k q_k \quad (\alpha_k \neq 0)$$

$$\alpha_1 \geq \alpha_2 \geq \cdots\cdots \geq \alpha_{m-1} \geq \alpha_m \tag{4}$$

α_k refers to the k number of feature value of the covariance S, q_k stands for the corresponding feature vector of the k number of feature value, m is the number of the feature value.

d) Take the first d number of feature vectors $P = (p_1, p_2, \dots\dots p_d)$ to make their corresponding feature value meet:

$$\frac{\sum_{i=1}^{d}\alpha_i}{\sum_{i=1}^{m}\alpha_i} \geq \theta \tag{5}$$

θ refers to the energy truncation ratio, which is 95% in this paper.

According to the above calculation, the ASM global shape model is:

$$S \approx \overline{X} + Pb \tag{6}$$

b is the principal component parameter, which is calculated by the formula $b = P^T \cdot (X_i - \overline{X})$, P is called principal component transformation matrix. ASM global model is a kind of shape model. It mainly shows the appearance shape of the face while gray level distribution of external feature points is described by the ASM local model.

3. Establishment of ASM local model

ASM local model represents gray level distribution of feature points. Each feature point gains a new position in every iterative process to form a new shape. That is why local model is built for each feature point. Set the feature point j (j=1,…,k) in the i (i=1,…,N) sample image, the steps to establish ASM local model are as follows:

Set p, t are the front and rear adjacent points of the feature point j. As figure 4 shows, through the feature point j, along with pt to make a vertical line q. The Gray value of the m number pixel found in the left and right of the center j on the linear q, combines the gray value of the feature point j to make a gray value vector 2m+1:

$$\boldsymbol{g_{ij}} = (g_{ij}1, g_{ij}2, \dots\dots g_{ij}2m, g_{ij}(2m+1))^T$$

1) Do differential operation on the gray vector $\boldsymbol{g_{ij}}$;

$$\boldsymbol{dg_{ij}} = (g_{ij}2 - g_{ij}1, g_{ij}3 - g_{ij}2, \dots\dots g_{ij}2m + 1 - g_{ij}(2m+1))^T \tag{7}$$

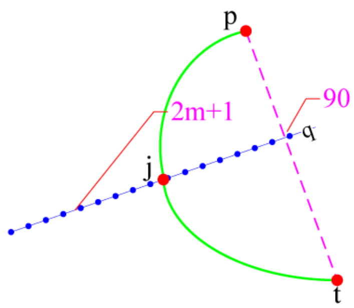


Figure 3. ASM local model

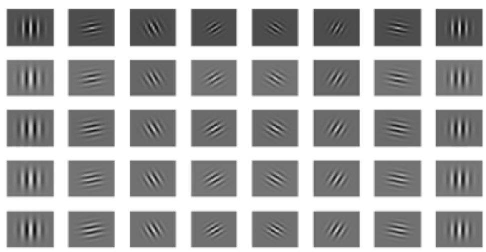


Figure 4. ASM-Gabor filter (5 scales and 8 directions)

2) Standardizing $\boldsymbol{dg_{ij}}$:

$$\boldsymbol{W_{ij}} = \boldsymbol{dg_{ij}}/(\textstyle\sum_{i=1}^{2m}|\boldsymbol{dg_{ij}}|) \tag{8}$$

3) Calculating the mean value $\overline{W_j}$ of $\boldsymbol{W_{ij}}$ and the variance S_j:

$$\overline{W}_j = \frac{1}{N}\sum_{i=1}^{n} g_{ij} \tag{9}$$

$$S_j = \frac{1}{n}\sum_{i=1}^{n}(W_{ij} - \overline{W_j})^T (W_{ij} - \overline{W_j}) \tag{10}$$

The feature information described by the mean value $\overline{W_j}$ and the variance S_j is the local gray model of the feature point j.

3.1. Fusion of Gabor and ASM

As Gabor wavelet feature transform has strong robustness to illumination, the paper adds local wavelet feature transform to the ASM feature so as to enhance the rate of face identification under the non-uniform illumination:

Two dimensional function expression of Gabor is:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp(-\frac{(x'^2 + \gamma'^2 y^2)}{2\sigma^2}) * \exp(i(2\pi\frac{x'}{\lambda}) + \psi) \tag{11}$$

Among them

$$x' = xcos\theta + ysin\theta\ , y' = -xsin\theta + ycos\theta;$$

λ refers to the wavelength, usually more than 2; θ stands for the direction, whose range of values from 0 to 360 degrees; ψ means phase shift, whose range of values is $(-180^o, 180^o)$; γ represents space aspect ratio, usually 0.5; σ is Gauss factor standard deviation of Gabor function; Choosing different function parameter can produce two dimensional Gabor wavelet in various forms .

As for ASM, there is sequence of front and back relation among feature points. Therefore, the paper puts forward that the real edge direction of the current feature points is replaced by the normal direction of the gradient of the two feature points. In the screenshot of part of the outer contour of face, gradient angle is calculated for the feature points from j-1 to 8 neighborhood . The maximum gradient angle is chosen to be θ_1. Similarly, the gradient angle of j+1 is θ_2. So the Gabor wavelet directional angle of j is $(\theta_1+\theta_2)/2$.

Therefore, the way to fuse Gabor feature model and ASM local feature goes like this on the whole: at first, using Gabor waveletwith different scales in the selected direction to extract features on each feature point; then calculating the average gradient direction of the adjacent two points on each feature point j (j=1,…,k) to be the direction of Gabor imaginary part function. If there are S number of scales, it means that there are S number of Gabor imaginary part function $G^1, G^2, \ldots\ldots, G^S$

When 2m+1 number of pixel points $\boldsymbol{g_{ij}}$ are derived from the ASM local feature model, through the i (i=1,…,n)set of image, along the vertical direction of the connecting line in the vicinity of the point, m number of pixel points should be chosen on both sides of the feature points. These 2m+1 number of pixel points convolute with $G^1, G^2, \ldots\ldots G^S$ respectively, and then 2m+1dimensional Gabor feature value vector is obtained of S group:

$$\mathrm{GM}_{ij}^S = \left(\mathrm{gm}_{ij1}^s,\ \mathrm{gm}_{ij2}^s, \ldots\ \mathrm{gm}_{ij(2m+1)}^s\right)^T$$
$$s = 1,2, \ldots; \tag{12}$$

Standardizing GM_{ij}^S:

$$C_{ij}^S = \frac{\mathrm{GM}_{ij}^S}{\sum_{i=1}^{2m+1}|\mathrm{GM}_{ij}^S|}\ , s = 1,2\ldots, S \tag{13}$$

From this local ASM-Gabor feature information model corresponding to the feature point j is gotten: they are the mean and the covariance.

$$\overline{C_j^S} = \frac{1}{N}\textstyle\sum_{i=1}^{N} C_{ij}^S \tag{14}$$

$$Ccov_{ij}^S = \frac{1}{N}\sum_{i=1}^{N}(C_{ij}^S - \overline{C_j^S})\left(C_{ij}^S - \overline{C_j^S}\right)^T,$$
$$s = 1,2, \ldots, S \tag{15}$$

From formula (13-15) the decision function of the point's new position is:

$$f_j(i) = \left(W(i) - \overline{W_i}\right)^T S_j^{-1}\left(W(i) - \overline{W_i}\right) + \sum_{s=1}^{S} w_j^s(C(i) - \overline{C_j})^T Ccov_j^{s-1} w_j^s(C(i) - \overline{C_j}) \tag{16}$$

Each time searching for the new position iteratively, the feature point will move at the normal direction to make the decision function minimum, and then gain its new position.

S is valued 5 in this paper, which is 1～5 scales in 8 fixed direction as shown in figure 6. The window size of their corresponding discrete function Gabor are 3×3,5×5,7×7,9×9,11×11,13×13. As figure 4 shows.

3.2. Eye location

In order to enhance the accuracy rate of eye location, the paper puts forward the method of connecting local ASM algorithm and integral projection technique is used to realize dual positioning of eye. Results from the two kinds of methods (according to minimum variance principle) multiply a certain weight respectively, and finally the position of eye on the basis of weight parameter is figured out.

Establishing an eye shape model based on the shape feature is the first step, that is, picking six vertices of the eye as shape model. The first eye location is finished by the use of local information feature and shape feature of ASM model and the gravity coordinate of the eye in reticular region is calculated at the same time. Then the eye region located by the ASM algorithm will go through binarization and integral projection. The second eye location coordinate is realized by the peak of projection curve. Finally, after related weight is calculated according to minimumvariance principle, the final eye coordinate will be obtained.

Set G(x,y) stands for the gray value of the image (x,y), horizontal integral projection H(x) in the image $[y_1, y_2]$ region and vertical integral projection V(y)in the $[x_1, x_2]$ region can be expressed like:

$$H(x) = \frac{1}{(x_2 - x_1)} \sum_{x=1}^{x_2} G(x, y) \qquad (19)$$

$$V(y) = \frac{1}{(y_2 - y_1)} \sum_{y=1}^{y_2} G(x, y) \qquad (18)$$

The eye position will be gained by the extreme point coordinate of horizontal gray curve projection after doing some horizontal integral projection on the binarizated face image and normalizing the projection curve.

Guaranteeing the weight parameter: set the gravity coordinate (x_h, y_h) of the eye region guaranteed by ASM, the calculating result (x_g, y_g) of gray integral projection and the right eye coordinate (x, y), when the variance function f_v reaches the minimum and keeps stable in the iterative process, the gained weight parameter a,b are the final weight parameter.

$$f_v = \sqrt{a[(x_h - x)^2 + (y_h - y)^2] + b[(x_g - x)^2 + (y_g - y)^2]},$$

$$(a+b=1) \qquad (19)$$

By the formula (20) to obtain the final eye location coordinates (x_d, y_d):

$$\begin{cases} x_d = a x_h + b x_g \\ y_d = a y_h + b y_g \end{cases} \qquad (20)$$

Figure 5 shows the gray integral projection of the eye region on the horizontal and vertical direction. The figure indicates that the transverse and vertical coordinates are located based on the coordinates of wave peak of the horizontal and vertical projection.

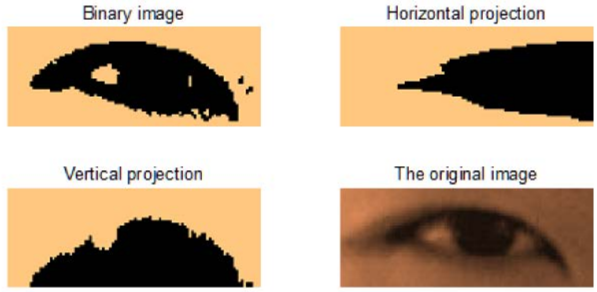
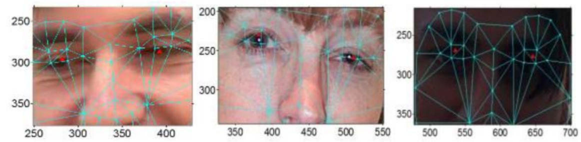
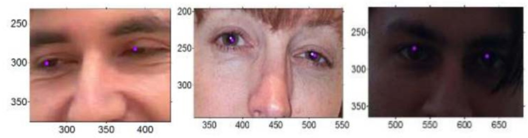


Figure 5. The gray integral projection of the eye region on the horizontal and vertical direction

Figure 6 is the comparison between the result of eye location by ASM local model and gray integral projection separately (a) and the final result (b) by certain weight combination in the paper. It shows that the method put forward in the paper improves to some extent compared with the other two methods.



(a) the result of eye location by ASM local model and gray integral projection separately



(b) Positioning results of weight combination method in the paper

Figure 6. The comparison of Eye recognition results

4. Experimental results and analysis

The experiment applies FERET and Color face image library of the California institute of technology, which are widely used in face recognition field. 1300 face images in multi-pose and different illumination are selected, 1000 of which serve as training samples and 300 of which are taken as testing samples. They are divided into three groups, frontal face under non-uniform illumination, face under side illumination and multi-pose face under non –uniform illumination. Each group has 100 face images. All the images are marked manually 68 key feature points. Configuration of the experimental program PC are: cpui7-4710mq, frequency 2.5GHZ, running software MATLAB 2012a.

In this paper formula (21) is used to assess the recognition results of ASM algorithm good or bad:

$$d = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{n}\sum_{j=1}^{n} dist(P_{ij}, P'_{ij})\right) \quad (21)$$

In the formula (23), N refers to the total number of testing images while n stands for the number of face key feature points (n is 68 in the paper). P_{ij} is the coordinate of the j feature point marked manually in the testing images. P'_{ij} is also the coordinate of the j feature point located automatically by algorithm and dist(·,·) means Euclidean distance between the two. The smaller the d is, the better recognition effect of algorithm is.

In order to test the validity of the algorithm of the paper 3 groups of testing samples needs taking testing detection and then analyzing like this:

(A) Do face recognition test under non-uniform illumination on group 1 (frontal face under non-uniform illumination), group 2 (face under side illumination) and group 3 (multi-pose face under non –uniform illumination) used the traditional ASM algorithm and ASM-Gabor method put forward in the paper respectively. Part testing results are shown in figure 7 and figure 8. they reflect that the recognition effect under the non-uniform illumination of ASM model fused with Gabor feature improved a lot compared with the traditional ASM algorithm.

Figure 9 shows that the method of the paper on three groups improves compared with the traditional ASM algorithm, especially significant enhancement on under non-uniform illumination multi-pose faces. From figure 9 it is shown that the face location result rises by 11.79% by the algorithm of the paper compared with the traditional ASM algorithm.(shown in table 1).

(B) Respectively using ASM local model and weight parameter combination method to do location test on eyes. Figure 10-11 shows the results. Figure 10 is the eye region guaranteed by ASM six points, red dot represents the gravity of the six points. Figure 11 is the eye region guaranteed by the algorithm of the paper while the red dot is the final coordinate.

Figure 12 shows that the method of the paper on three groups improves compared with the traditional ASM algorithm. From figure 12 it is shown that the local eyes location result rises by 18.35% by the algorithm of the paper compared with the traditional ASM algorithm.(shown in chart1).

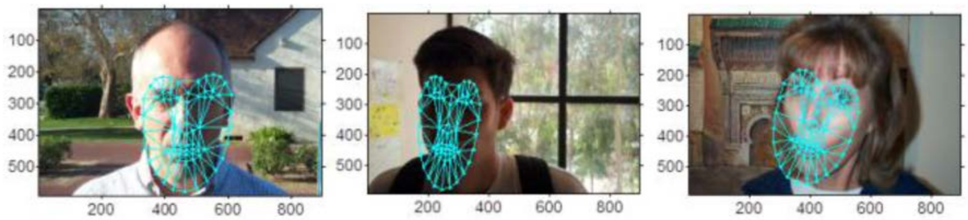


Figure 7. The result of eye location by ASM local model

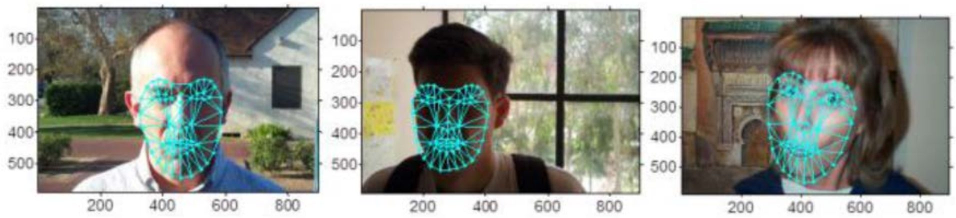


Figure 8. The result of eye location by ASM-Gabor model

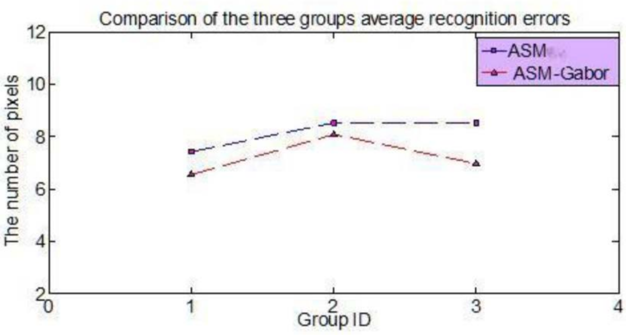


Figure 9. the comparison of the three groups average recognition errors

Table 1. Analysis of global face recognition errors (The error unit is pixel)

Method	Group1	Group2	Group3	Average error
ASM	7.4403	8.5336	8.5284	8.1674
ASM-Gabor	6.5405	8.0958	6.9749	7.2037
Improved	12.09%	5.13%	18.21%	11.79%

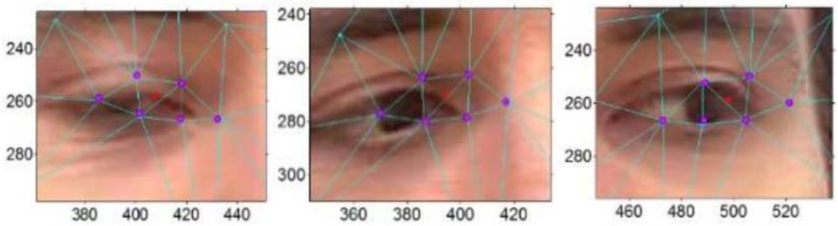


Figure 10. The result of eye location by ASM local model

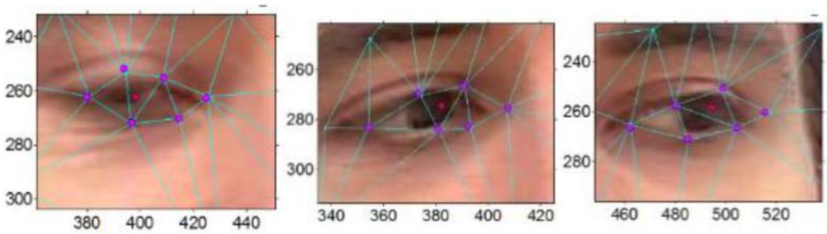


Figure 11. The result of eye location by weight parameter combination method

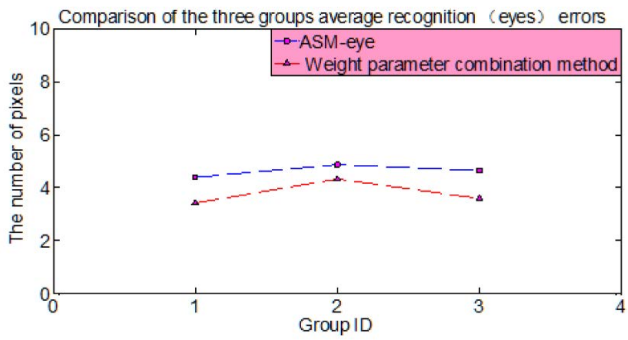


Figure 12. The comparison of the three groups average position errors

(C) In order to test the robustness of the algorithm the paper locates the face and eye of muti-pose under non-uniform illumination. Part results are shown in figure 13-14. (a) is the experiment result of traditional ASM while (b) is the experiment result of this paper.

From figure 13 and figure 14 it is clearly shown that the algorithm of the paper can well locate the face and eye even in big change of muti-pose under non-uniform illumination.it makes great progress compared with the traditional ASM algorithm.

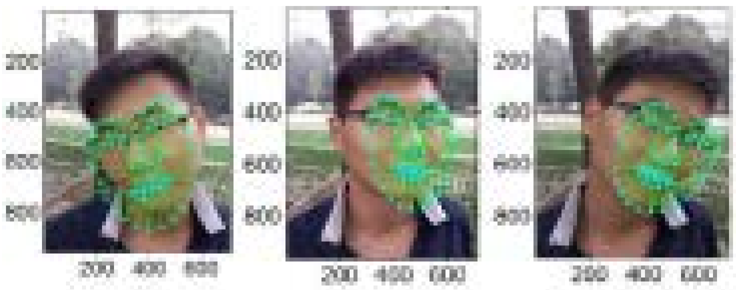


Figure 13 (a). The global experiment result of traditional ASM

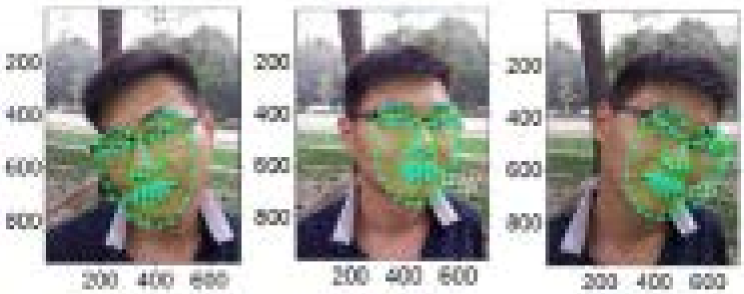


Figure 13 (b). The global experiment result of this paper

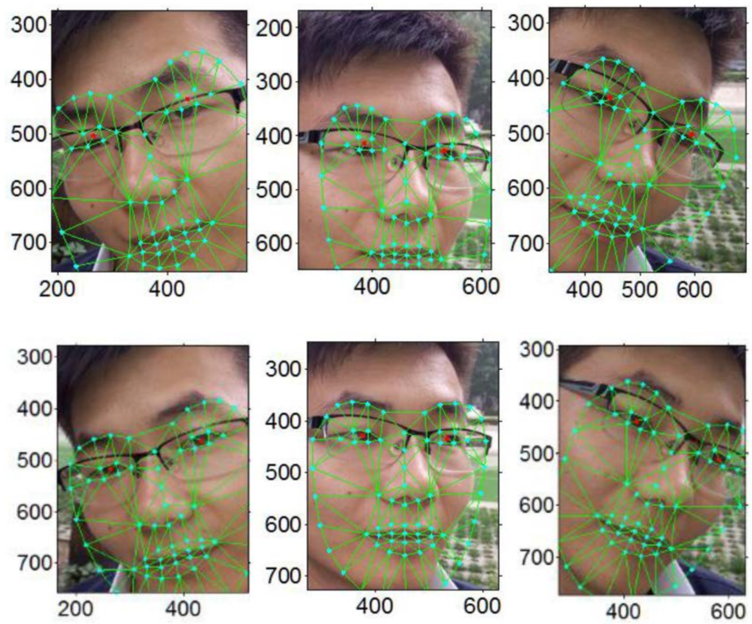


Figure 14 (a). The local experiment result of this paper

From the formula (22)

$$P = \frac{d_{ASM} - d_{ASM-Gabor}}{d_{ASM}} \times 100\% \quad (22)$$

It can be figured out that compared with the traditional ASM algorithm, the algorithm of the paper can rise location monitoring of face and eyes by 11.79% and 18.35% respectively, especially significant enhancement on under non-uniform illumination multi-pose faces. (data shown in table 1 and table 2)

Table 2 Analysis of local eye position errors (The error unit is pixel)

Method	Group 1	Group 2	Group 3	Average error
ASM	4.3927	4.8804	4.6471	4.64
Weight parameter	3.4341	4.3343	3.5961	3.7881
Improved	21.82%	11.13%	22.61%	18.35%

Conclusion

With regard to the fact that the accuracy of eye location of muti-pose under non-uniform illumination by ASM algorithm is non high, the paper puts forward the method of combining Gabor features in the direction of gradient mean and local ASM model, which can upgrade the robustness under the condition of non-uniform illumination. Also, at the face region, the other method of connecting local ASM eyes template and integral projection technique is used to realize dual position of eyes. On the basis of the results of the two kinds of methods, the paper puts forward adjusting their result weight by variance function and finally figure out the position of eyes according to weight parameter. The experiment shows that the algorithm of the paper can reach effective recognition face and location of eye region under non-uniform illumination. Meanwhile, the algorithm of the paper can rise location monitoring of face and eyes by 11.79% and 18.35% respectively (ASM) .Therefore, the paper has guiding significance to eye location, driving fatigue detection and other application.

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