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An Efficient Recognition Method for Drivers' Eye States

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Abstract: In order to decrease the influence on the recognition of for drivers' eye states when the lightness or view angle change suddenly, a new algorithm in this study is proposed to improve the recognition rate, which combines Kanade-Lucas (K-L) optical algorithm with Adaboost cascade classifier. This algorithm recognizes and saves the Harris corner using Adaboost algorithm. Those saved corner features would be tracked using K-L algorithm, if Adaboost algorithm did not recognize them again. The method improves the recognition rate and reduces the iterate computation of identification. Because, it is difficult to distinguish the eye with the eyebrow or the eye-rim, the second threshold segmentation algorithm is advanced to decrease the initial value of the global threshold and the second threshold is set to improve the recognition rate. Freeman chain code is used to search the contour of the recognized eye and three states of the drivers' eye are determined according to Elliptic equations. The experiments showed that the method can decrease the influence of the lightness and view angle and improve the recognition precision efficiently.

Key words: Kanade-Lucas algorithm, global threshold, freeman chain code, elliptic equations, recognition rate

INTRODUCTION

Adaboost cascade classifier technology (Wang *et al*., 2009; Yun and Ling, 2009; Li *et al*., 2009) is used to recognize the drivers' eye states in the recent years. This method can obtain some well-pleasing results through training lots of positive samples and negative samples. But it can not be sure that most of the negative samples are filtered and all the positive samples pass those cascade classifiers. The change of lightness or view angle exerts serious influence on the eye recognition and also, brings the recognition rate down tremendously. So, how to reduce the influence of these factors? The study proposes a new method, which is combined Kanade-Lucas (K-L) algorithm (Chuntao *et al*., 2009; Rosner, 2007) with Adaboost cascade classifier algorithm. This new method uses K-L algorithm to track the eye features, which have been recognized, saved and updated by Adaboost algorithm. So, the method reduces the eye recognition error, which is caused by the change of lightness or view angle. And the repeated recognition will be decreased. Because it is difficult to distinguish the eye with the eyebrow or the eyelid only through Global threshold segmentation algorithm, second threshold segmentation algorithm is proposed. The method decreases the initial value of Global threshold and sets second threshold in the iterative cycle. Therefore, it improves the segmentation results. Finally, Freeman chain code is used to find the contour and the three states of the eye is determined according to the elliptic equations. The experiments show that the method is able to detect the eye states of drivers in real-time accurately.

ADABOOST CASCADE CLASSIFIERS

AdaBoost algorithm is proposed based on boosting algorithm by Yoav *et al*. (2004). Those designers need accumulating some new week classifiers until to reach the error rate set enough small. Namely, these classifiers are constructed by using each Haar-Like feature and expressed by the threshold function (Yoav *et al*., 2004) as the followings:

$$h_i(x) = \begin{cases} 1 & \text{if } f_i(x) > \theta_i \\ 0 & \text{if } f_i(x) < \theta_i \end{cases} \tag{1}$$

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In which, θ_i are the threshold, x are the sub-window of image sample, $f_i(x)$ are the Haar-Like rectangle features for x. The features of the fewest misrecognition samples, f_i, are found by computing $h_i(x)$ and $h_i(x)$ are the best week classifier. So, a lower threshold is able to lead to a higher classifier, but its misrecognition rate is higher too. In the contrast, the higher threshold can produce a classifier with the lower recognition rate.

If the computation cycle were increased, the error of the final strong classifier would be small so that to improve the recognition precision from the traits of Adaboost algorithm. But with the increase of T, the number of week classifier is increasing too and the computation burden will be strengthened. So, the cascade classifiers are used to construct a stronger classifier and the stronger classifier will be sorted from the bigger to the smaller in order to improve the efficiency. Supposing the misrecognition rate of cascade classifiers F are the product of each cascade classifier, f_i and the total recognition rate of cascade classifiers, D, is the product of each cascade classifier, d_i. Namely:

$$F = \prod_{i=1}^{N} f_i \tag{2}$$

$$D = \prod_{i=1}^{N} d_i \tag{3}$$

In which, N is the number of cascade classifiers.

With the number of cascade classifiers increasing, the misrecognition rate and recognition rate are all reduced. Many of face areas will be excluded by error. So, it is infeasible to increase the number of cascade classifiers to improve the recognition rate. Reducing the threshold, θ, can improve the recognition rate according to Eq. 1, but the misrecognition rate is increased too. So, it is impossible to reduce the misrecognition rate and improve the recognition rate at the same time, no mater what the number of cascade classifier is improved or the threshold is reduced. It is important that how to restrict those factors to influence on the fatigue status detection for drivers' eyes.

THE DETECTION ALGORITHM OF HARRIS CORNER

The Harris corner is an important local behavior, which influences plenty of contour information. Generally the location of tremendous change of lightness is chosen as Harris corner. In this study, Harris corners is used to recognize the corner features of the eye.

Harris operator is proposed by James *et al.* (2006). The method uses the first order difference of one image to compute square matrix of average graded for each pixel and analyzes the position of Harris corner by the characteristic value. Because the differential operation enlarges the noise generally. At first, smooth the image using Gauss algorithm, then set I(x, y) denoting the graded value of the coordinate (x, y), at last the graded of lightness is computed by Sobel operator. Figure 1a and b show the horizontal operator and vertical operator for Sobel operator:

Supposing I_x is the graded value in x direction, I_y is in y direction, the equitation of I_x and I_y can be obtained by Sobel operator as the following equation:

$$I_x(x,y) = [I(x+1,y-1) + 2I(x+1,y) + I(x+1,y+1)] - [I(x-1,y-1) + 2I(x-1,y) + I(x-1,y+1)] \tag{4}$$

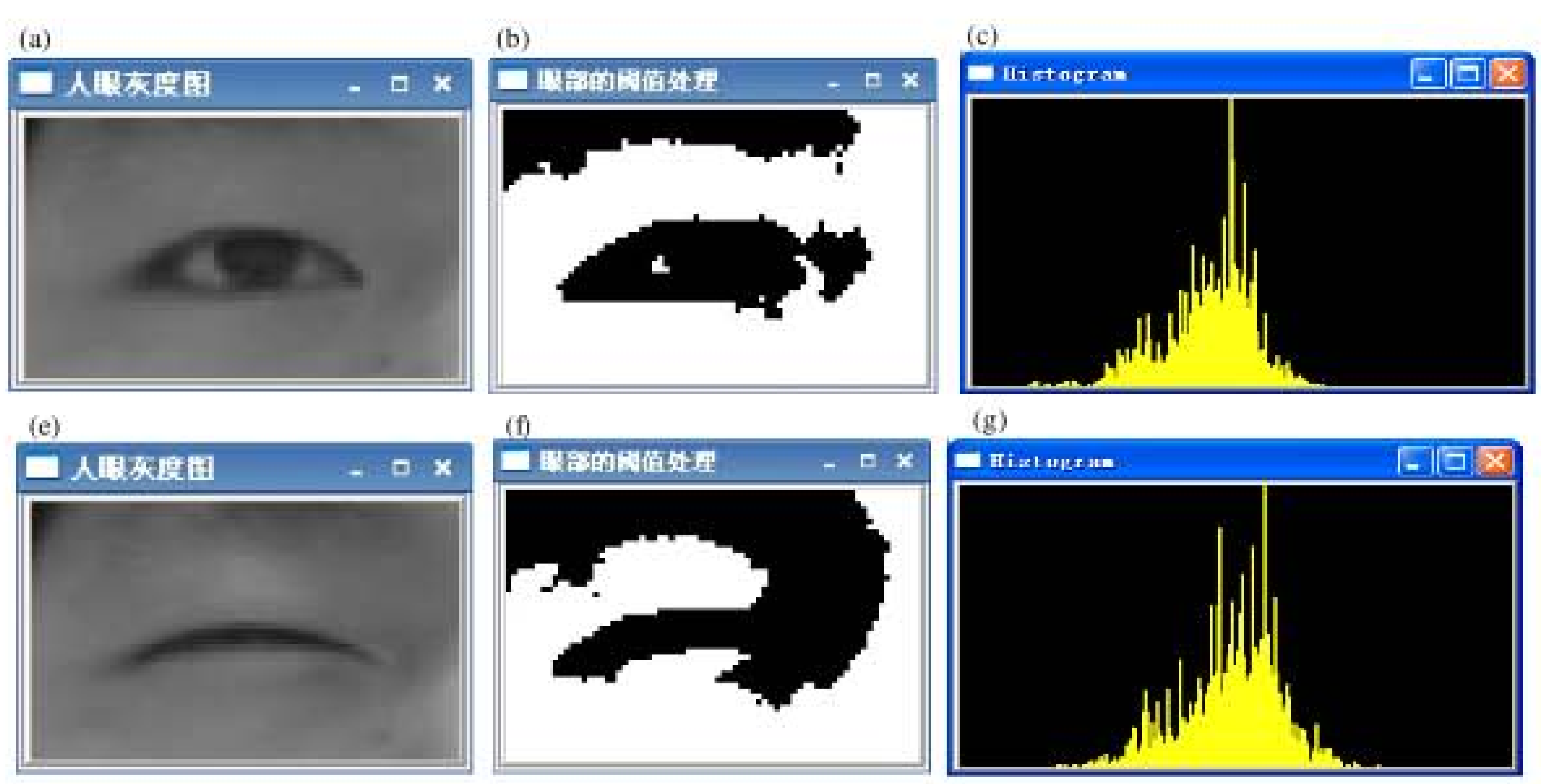

Fig. 1: The result of segmentation using basic global adaptive threshold

$$I_y(x,y) = [I(x-1,y+1) + 2I(x,y+1) + I(x+1,y+1)] - [I(x-1,y-1) + 2I(x,y-1) + I(x+1,y-1)] \quad (5)$$

Through Eq. 4 and 5, the difference correlation matrix, M, for each pixel of one image, can be computed:

$$\mathbf{M} = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (6)$$

Carlos and Megherbi (2005) has proved that if the two characteristic value of difference correlation matrix for each point was very large the point would be regarded as Harris corner. So, compute the characteristic value of each pixel matrix and keep the point, whose local characteristic value near the field of 3×3 matrix is the largest one. According to the traits of the image, set the factor of the traits, exclude the Harris corner, which is smaller than the set factor, then keep the maximum that Euclidean distance is smaller than the set value.

THE K-L OPTICAL ALGORITHM

After the Harris corner has been detected, the Harris features can be tracked and located using K-L algorithm. K-L algorithm finishes the location of the eye by computing the least value of sum of grey-scale squares difference between near two frames, $\in$. namely the smallest point of lightness difference between the current frame and the last frame. This point is regarded as the same point with the feature point tracked.

Supposing the lightness value of the current frame (X, Y) is I(X, Y, T+t), the prior frame is (X-x, Y-y) and its lightness is I(X-x, Y-y), the lightness is never changed (Rosner, 2007).

$$I(X,Y,T+t) = I(X-x, Y-y, T) \quad (7)$$

The noise is introduced because of the lightness change generally, set the noise, n(X, Y):

$$I(X,Y,T+t) = I(X-x, Y-y, T) + n(X,Y) \quad (8)$$

The integral of n(X, Y) square is $\in$, sum of grey-scale squares difference. Namely:

$$\varepsilon = \iint_V n^2(X,Y)\,dX\,dY = \iint_V [I(X,Y,T+t) - I(X-x,Y-y,T)]^2\,dX\,dY \quad (9)$$

The aim of K-L algorithm is to find the unknown quantity, $d = (dx, dy)^T$, which makes $\in$ the smallest.

Set $X = (X,Y)^T$, $A(X-d) = I(X-x, Y-y)$, $B(X) = 1(X,Y,T+t)$, so when d = 1 and the ratio with X can be ignored, A(X-d) is expanded based on the Taylor first order expansion and the higher order term is ignored. The followings can be gotten.

$$A(X-d) = A(X) - (A'_x(x) - A'_y(x))d \quad (10)$$

In which, A'_x and A'_y is the partial derivative in x-axis and y-axis, respectively. Set $g = (A'(X)_x, A'_y(X))^T$.

Take Eq. 10 into Eq. 9 and get the followings:

$$\varepsilon = \iint_V [B(X) - A(X) + g^T d]^2\,dX \quad (11)$$

Set the followings to get the minimal value, θ.

$$\frac{\partial \varepsilon}{\partial d} = \iint_V 2[B(X) - A(X) + g^T d] \times g\,dX = 0 \quad (12)$$

Get the following Eq 13:

$$\left(\iint_V g g^T dX\right) d = \iint_V (B(X) - A(X)) g\,dX \quad (13)$$

Namely:

$$\iint_V \begin{pmatrix} A'_x(X)^2 & A_x(X)A_y(X) \\ A'_x(X)A'_y(X) & A_y(X)^2 \end{pmatrix} dX \begin{pmatrix} x \\ y \end{pmatrix} = \iint_V (B(X) - A(X)) \begin{pmatrix} A'_x(X) \\ A'_y(X) \end{pmatrix} dX \quad (14)$$

The amount of displacement, (x, y), relative to the last frame, can be obtained by Eq. 14 to track those features.

The Harris corners are detected and saved in some field of each one frame when the eye features are recognized. While Adaboost algorithm can not find the eye, the saved corners will be tracked using K-L algorithm. So long as AdaBoost algorithm was able to recognize the eye one time, K-L algorithm would be used to track those features. The following is the process in details.

- **Step 1:** Read one frame from the video
- **Step 2:** Detect the eyes using Adaboost algorithm
- **Step 3:** If the eyes are detected and located at first, the Harris corners are saved and updated to locate the position of the eye using K-L algorithm
- **Step 4:** Read the next frame from the video
- **Step 5:** If the location of the eye is not detected, the location change of Harris corners is detected using K-L algorithm

- **Step 6:** ELSE detect the eyes using Adaboost algorithm
- **Step 7:** Recognize the subsequent states of the eye

The recognition rate of Adaboost algorithm decides the precision of K-L algorithm according to above the analysis. The recognition rate of Adaboost algorithm is higher and the rate of misrecognition is lower. So, the recognition rate of K-L algorithm is higher too.

THE ACQUISITION OF THE THRESHOLD

After the area of the eye is determined, the image segmentation technology is used to process the image of the eye so that to get the further information of the eye. Here, a general method of image segmentation is introduced. It is basic global threshold method (Wang *et al*., 2009).

Basic global threshold method finds the threshold T by the histogram based on Global threshold segmentation. The threshold chooses the wave trough of histogram, where the lightness changes obviously. This position is also the dividing point between the background and the aim. The algorithm in details is given as the followings:

- **Step 1:** Choose the initial value of T. Generally use the average lightness of the image
- **Step 2:** Use T to compute the average pixel value, dimmer than T as μ_1, or brighter than T as μ_2
- **Step 3:** Compute the new threshold

$$T = \frac{(\mu_1 + \mu_2)}{2} \tag{15}$$

- **Step 4:** Repeat Step 2 and 3 until the difference of both T less than the set value t_0

Figure 1 shows that the segmented results while the eye close or open using the above algorithm. The Fig. 1a is the grey-scale image under the normal state of the eye, the Fig. 1c is its corresponding histogram. So here is the equitation T = 83, the Fig. 1b is its 0-1 image. The Fig. 1d is the grey-scale image under the fatigue state of the eye, the Fig. 1f is its histogram. So here is the equitation T = 85, the Fig. 1e is its 0-1 image.

Figure 2 shows that it is not perfect for the image segmentation of the eye , because there is not distinct difference between the eye and the eyebrow, or the nose. From the histograms, such as the Fig. 1b, d, this method can separate the major of the eye exactly, but it is difficult to separate those areas of the similar lightness, so the improved method is taken as the followings.

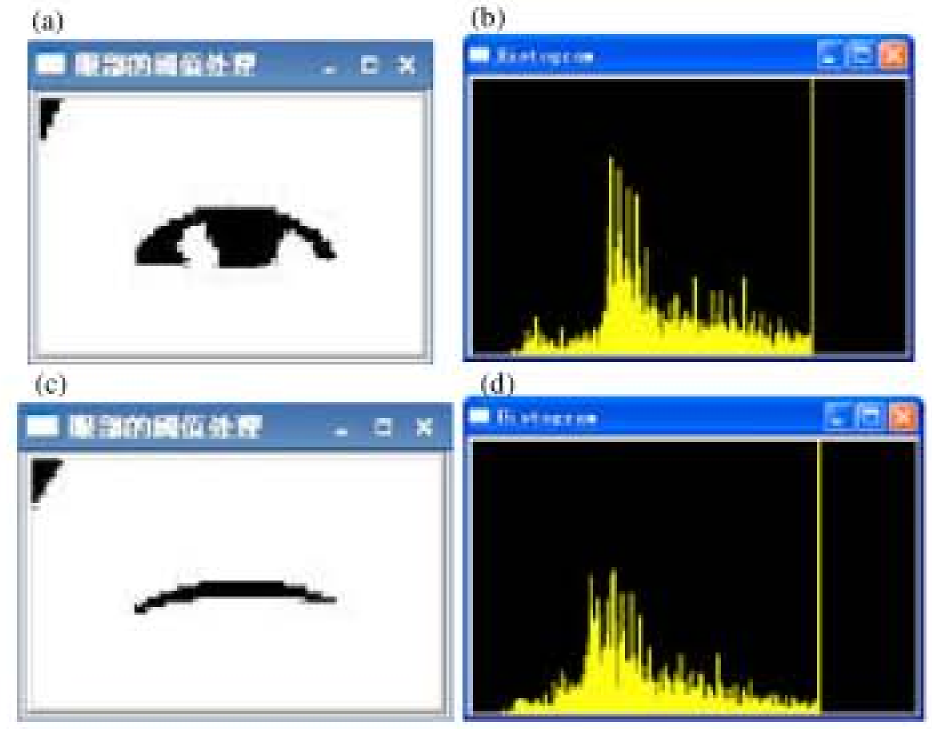

Fig. 2: The result of segmentation using improved global adaptive threshold

From the Fig. 1c there is another wave trough of histogram in the right part of global threshold, namely the grey-scale of eyes. This position can be regarded as the best location, where the eye and some shadows can be divided. So, after the global threshold, T_0, has been found, the second threshold is searched in the brightness field, $0 \sim T_0$.

Because the lightness of the eye is less than the eyebrow, the initial value, T, is reduced so that to decrease the final threshold. This method can highlight the part of the eye, enhance the value of t_0 and speed the computation. The algorithm in details is showed as the following:

- **Step 1:** Choose the initial value, set T = 0
- **Step 2:** Compute the average value of those pixels dimmer than T as μ_1, or brighter than T as μ_2
- **Step 3:** Compute the new threshold using Eq. 15
- **Step 4:** Repeat step 2 and 3 until the difference of both T less than the set value t_0

Figure 2a and b are the segmentation result for the Fig. 1a, d based on the improved global threshold algorithm. From its result of the processing it is better than the former algorithm. From the histogram the method can remove the background parts near the lightness of the eyes efficiently.

THE CONTOUR RECOGNITION BASED ON FREEMAN CHAIN CODE

After the area of the eye is segmented, its contour is found so that to determine the status of the eye. The freeman chain code is used to obtain the contour (Wulandhari and Habibollah, 2009; Bribiesca, 2008).

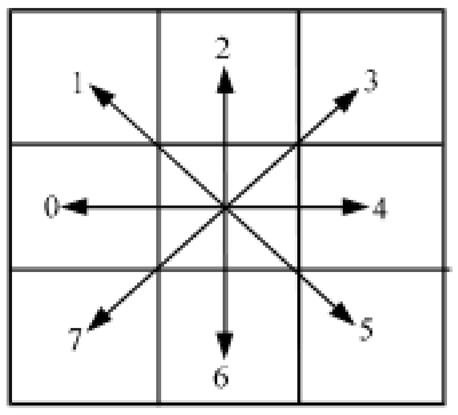

Fig. 3: The direction numbering of Freeman chain code

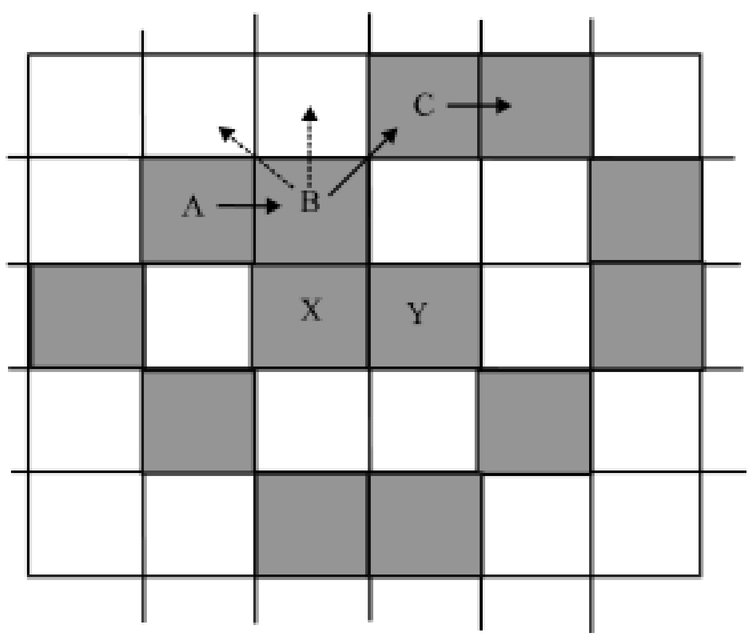

Fig. 4: The method of extracting the contours

- **Step 1:** Be sure of the contour direction (CW or CCW)
- **Step 2:** IF the different foregoing code is 0 (from A to B) rack the subsequent edging point of B point according to the orders, 1, 2, 3, 4, 5, 6, 7, 0, namely the direction of CW, as the Fig. 3 showed. Once grey value of C point is 0, it is the subsequent edging point. At the same time the other field is not detected. The X and Y in the Fig. 4 are not tracked to read, so the non contour pixel is masked. The same method continues for the other foregoing chain code
- **Step 3:** Save the C point and detect if the C point is the initial A; IF not, repeat Step2 from the point C; otherwise, track the recognition to end. The set of all the points is the contour of the whole image

From the above steps of Freeman chain code, the algorithm can clear the whole inner points, namely scanning every point of the image. If one point is black and the other eight points are also black, the point can be considered as the inner point. And it is deleted. After the searching process, the retained points compose the contour of image. The edge width is only one pixel by the method, so it is higher precision. Because the image, processed by 0-1 algorithm, has the whole contour, its edge is continuous.

THE STATUS RECOGNITION OF THE EYE BASED ON CONTOUR ANALYSIS

After the whole contour is obtained, it will be analyzed so that to determine the state of the eye further. The least square method is used to fit the elliptic equations.

The describing of elliptic fitting: Set the General Conic of elliptic equitation (Schleicher and Zagar, 2008; Xiao-Nan *et al*., 2009; Zhu and Runsheng, 2004):

$$Ax^2 + Bxy + Cy^2 + Dx + Ey + F = 0 \tag{16}$$

Set $\alpha = (A\ B\ C\ D\ E\ F)$, $x = (x^2\ xy\ y^2\ x\ y\ 1)^T$. So the elliptic equitation can be expressed as the followings:

$$F(a, x) = a \cdot x = 0 \tag{17}$$

Set $x = (x_i^2\ x_iy_i\ y_i^2\ x_i\ y_i\ 1)^T$, in which, (x_i, y_i) is one of the drawn contour, $F(a, x_i)$ is the algebraic distance from this point to the ellipse.

Supposing:

$$E(a) = \sum_{i=0}^{n} F(a, x_i)^2$$

is the quadratic sum of the algebraic distance from all the points to the fitting ellipse, so $\hat{\alpha}$, which makes $E(\alpha)$ the smallest, is the final coefficient of fitting ellipse. Namely:

$$\hat{a} = \underset{a}{\operatorname{argmin}} \left\{ \sum_{i=0}^{n} F(a, x_i)^2 \right\} \tag{18}$$

At the same time, a should satisfy the following conditions to ensure the equitation is ellipse, not liking the degenerated form as $\alpha = (0)_{6\times6}$.

$$B^2 - 4AC < 0 \tag{19}$$

It is difficult to find the solution of Inequality (19) because the optimality of Kuhn-Tucker can not ensure the solution exists. As Maurizio Pilu said that the constraint of inequality (Eq. 19) could be expressed as the followings for the parameters is changed according as the proportion:

$$4AC - B^2 = 1 \tag{20}$$

Maurizio Pilu proved that there was only one best solution for the ellipse fitting under this constraint.

The solution of ellipse fitting:

$$\text{Set } A = \begin{pmatrix} x_1^2 & x_1y_1 & y_1^2 & x_1 & y_1 & 1 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_i^2 & x_iy_i & y_i^2 & x_i & y_i & 1 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_n^2 & x_ny_n & y_n^2 & x_n & y_n & 1 \end{pmatrix} \text{ and}$$

$$D = A^TA$$

So there is the following Eq. 21.

$$E(a) = (Aa)^T(Aa) = a^T(A^TA)a = a^TDa \tag{21}$$

At the same time:

$$\text{Set } C = \begin{pmatrix} 0 & 0 & 2 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

So, Eq. 21 can be expressed as the followings:

$$a^TCa = 1 \tag{22}$$

So, the constraints of Eq. 18 and 20 can be expressed as the extreme condition of Eq. 21 under the constraints of Eq. 22:

$$2Da = 2\lambda Ca \tag{23}$$

$$a^TCa = 1 \tag{24}$$

So, one group of generalized characteristic value and eigenvector, (λ_i, α_i) of Eq. 23 can be gotten. For arbitrary constant k_i $(\lambda_i, k_i\alpha_i)$ is the solution of Eq. 23 in addition. Replace $k_i\alpha_i$ into Eq. 24 to get the followings:

$$k_i = \sqrt{\frac{1}{a_i^TCa_i}} \tag{25}$$

So, $\hat{\alpha}_i = k\alpha_i$ and D is positive definite, Eq. 23 has about the solutions of 6 groups, but Maurizio Pilu, etc. proved that there was only one group of characteristic value in the whole solutions greater than 0 and it is the final solution.

THE STATUS DETECTION OF THE EYE

The geometrical characteristics of elliptic equations are able to be computed to express the contour of the eye through the fitting elliptic method. The following is the deduction equation in detail.

$$x_c = \frac{BE - 2CD}{4AC - B^2} \tag{26}$$

$$y_c = \frac{BD - 2AE}{4AC - B^2} \tag{27}$$

$$a = 2\sqrt{\frac{-2F}{A + C - \sqrt{B^2 + \left(\frac{A-C}{F}\right)^2}}} \tag{28}$$

$$b = 2\sqrt{\frac{-2F}{A + C + \sqrt{B^2 + \left(\frac{A-C}{F}\right)^2}}} \tag{29}$$

$$\theta = \frac{1}{2}\arctan\frac{B}{A - C} \tag{30}$$

In which, the center coordinate of elliptic is (x_c, y_c), a is the major axis of the ellipse, b is the short axis of the ellipse, θ is the turn angle relative to horizontal axis.

THE ANALYSIS OF THE EXPERIMENT

Figure 5 shows the training results using AdaBoost cascade classifier. So, there is some misrecognition besides those features of the eye, because

Fig. 5: The detection result of using AdaBoost only on eyes

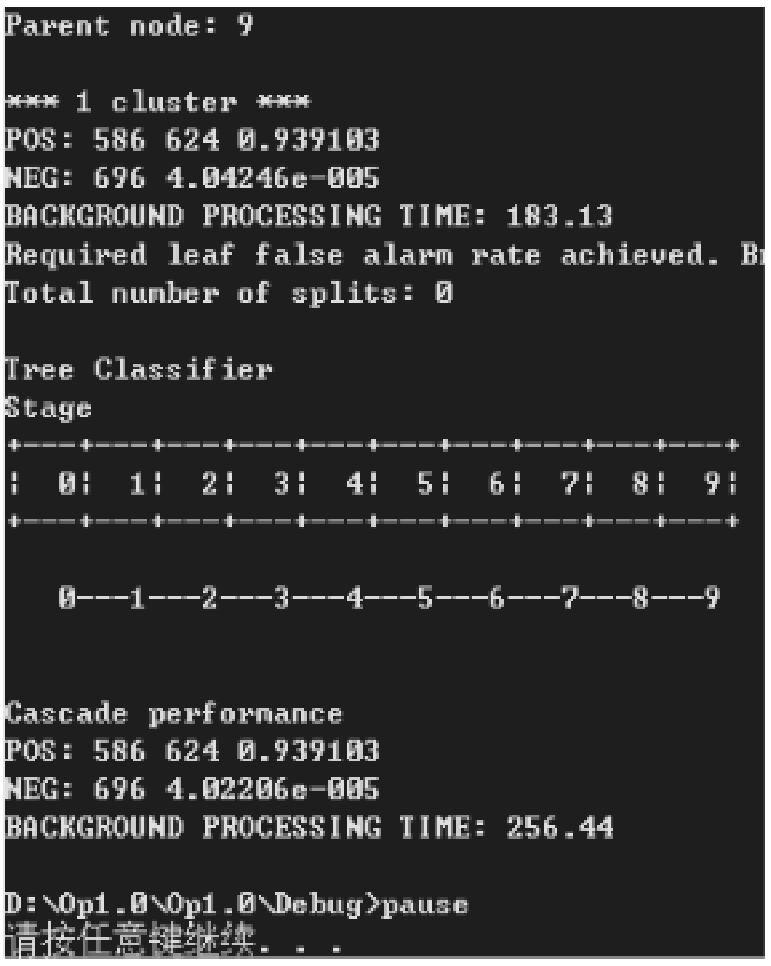

Fig. 6: Lane training using Adaboost cascade classifier

the open eye has many differences with the close eye. The threshold of Eq. 1 must be decreased in order to increase the recognition rate. However, the misrecognition rate is improved, especially in the tremendous change of lightness or view angle. So, it is difficult to satisfy the recognition need only using training the status classifiers of the eye. The recognition for the eye and the face should be taken at the same time.

Figure 6 shows the result of Adaboost cascade classifiers. The training time of the eye is 256.44 sec. The final number of cascade classifiers is nine and the final strong classifiers have 13 cascades. The number of right sample is 586 and the final recognition rate is about 93.91%.

Because the recognition rate of Adaboost algorithm is higher, the recognition result of Adaboost algorithm can be regarded as the actual position. So, the coordinates of Adaboost algorithm and K-L algorithm are saved and compared so that to analyze the reliability of K-L algorithm.

There are total more than 400 comparison results for the both algorithms in this experiment. Figure 7 and 8 show the correlation curves of both coordinates using K-L algorithm and Adaboost algorithm. From the pictures the recognition results of both algorithms are very similar. The both curves are almost consistent except some small differences near the No.150 frame. No error spreads with the increasing of the time. So, it shows that K-L algorithm is stable.

Figure 9 shows Euclidean distance curve between the center points. It can be seen the both algorithms detected the location of the eye. It is showed that the average distance of both eyes is about 5.5 pixels, the diagonal line of the eye' s rectangle area is about 80 pixels and the error is less than 7% and can be suitable for the recognition precision. From the Fig. 9 there are some bigger errors from the frame of No.150 to No.180 frame, about average 15.3 pixels, nearly 20% of the diagonal line of the eye' s rectangle area. It is result of the local maximum. The K-L algorithm can track those features in the smaller field exactly. But while the distance changes tremendously, such as the obvious lightness change or the intense tremble and so on, it is difficult for K-L algorithm to track the corners and some errors are produced. However, the recognition rate of Adaboost algorithm is higher generally and can save and update those corner features, which have been recognized by Adaboost algorithm. Therefore, the whole recognition precision has been improved.

Figure 10a and b show that the main interface of recognition based on K-L algorithm and Adaboost algorithm. Figure 10a shows the positive or negative samples are trained to get the cascade classifiers by using Adaboost algorithm. Further, the right location and the three states of the eyes are decided. From the Fig. 10b the Hairs corner features are tracked by using K-L algorithm based on Adaboost cascade classifiers. Though Adaboost algorithm could not recognize the eye states sometimes, the Hairs corner features remembered those features recognized by Adaboost algorithm. So, the K-L algorithm saves the recent location and moving direction of the eye and finds the final location. Therefore, the method may decrease the influence on the eye recognition from the change of lightness or view angle in some degrees and improves the robust of eye recognition.

Figure 11a-l shows the recognition of the eye states in the different lightness, according to the initial location recognized by Adaboost algorithm as Fig. 10. Figure 11a-d is the result in the normal lightness, the Fig. 11e-h is in the dim lightness and the Fig. i-l is in the bright lightness. So, the K-L algorithm can track those features recognized by Adaboost algorithm in different lightness or view angle. This method has the ability of scale invariant feature transform and affine invariant and can adapt to the state recognition for drivers' eye in the driving room.

As the Fig. 12 is showed, the eye states can be determined by the value of a/b. Figure 14 shows the contour of the eye. From the Fig. 13, about 200 values of a/b is given. The date shows that the eye is normal, when $a/b<3.5$; the eye is fatigue, when $3.5<a/b<4.2$; the eye is close, when $a/b>4.2$.

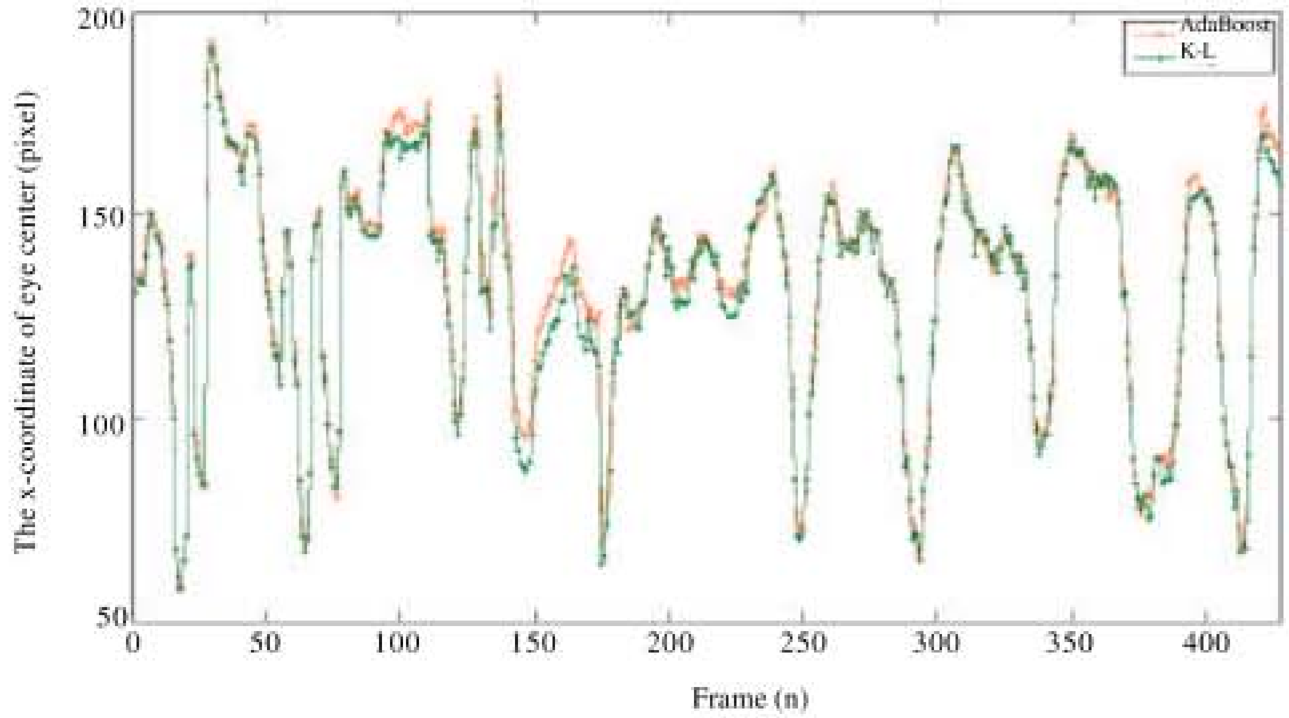

Fig. 7: The Correlation curve of the eye center x-coordinate detected by Adaboost and K-L algorithm

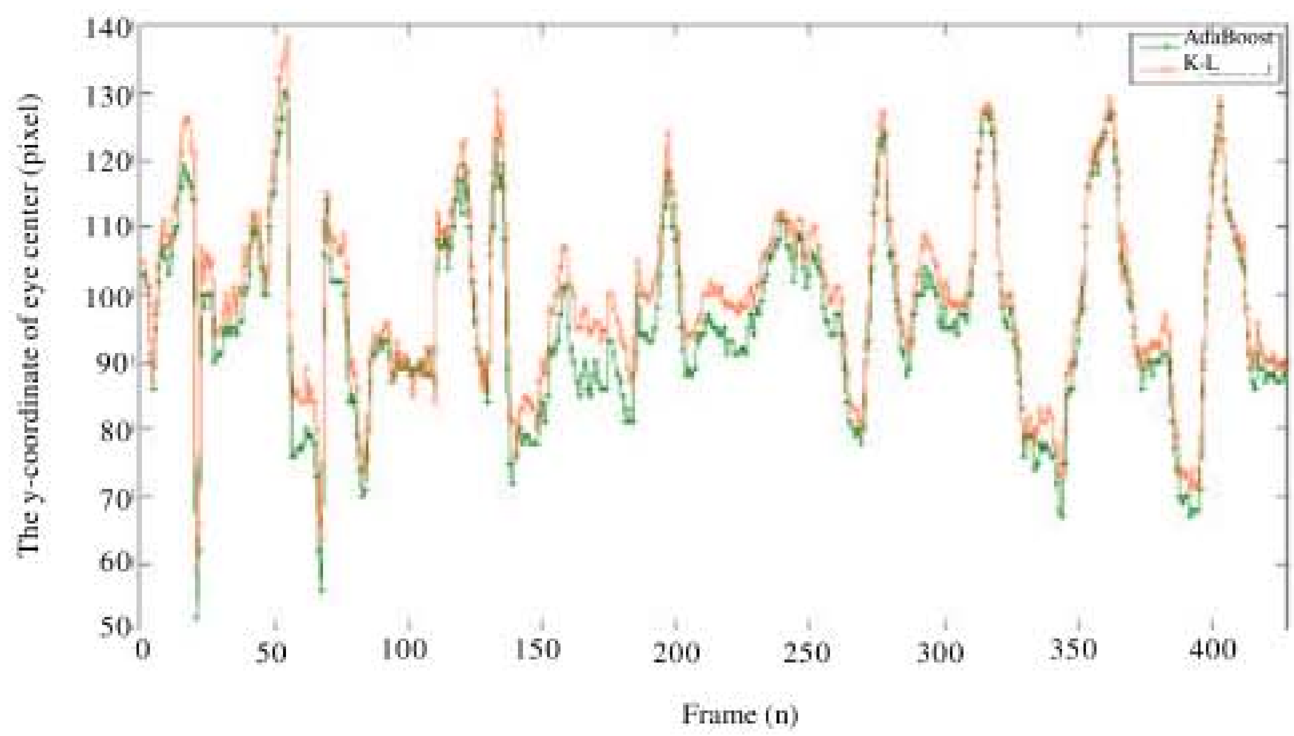

Fig. 8: The Correlation curve of the eye center y-coordinate detected by Adaboost and K-L algorithm

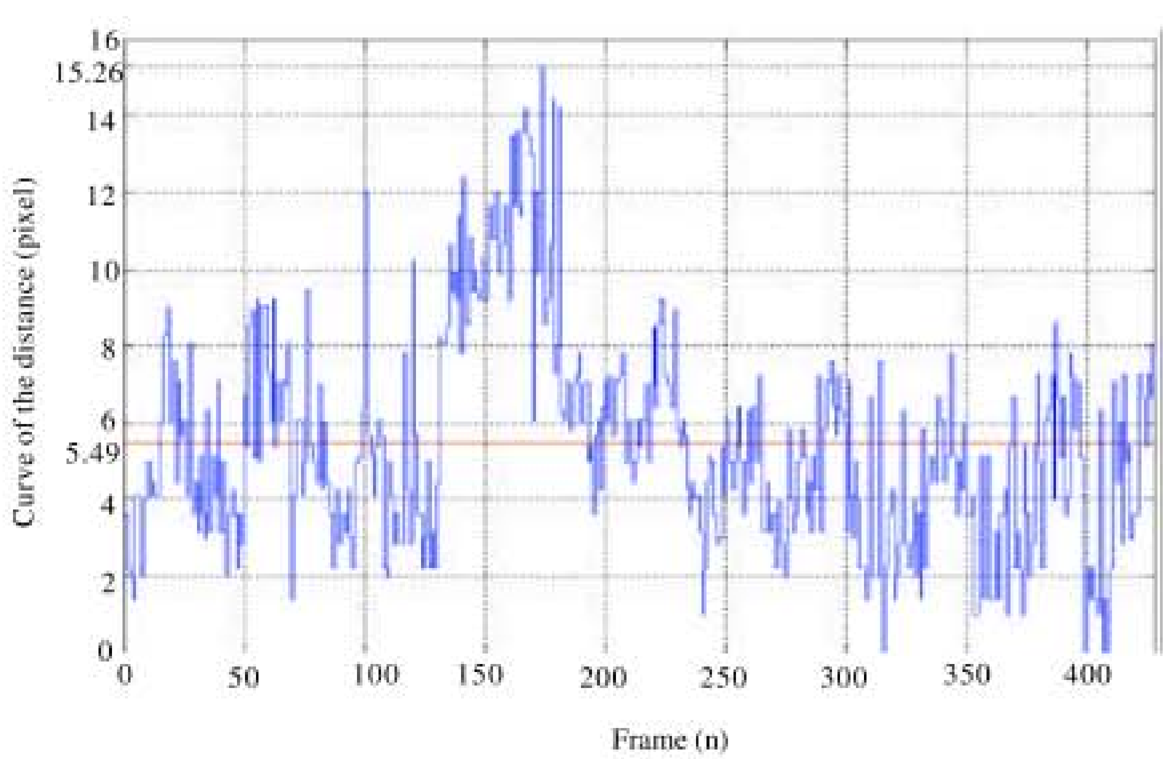

Fig. 9: Curve of the distance between the center of the eye detected by the two algorithm in each frame

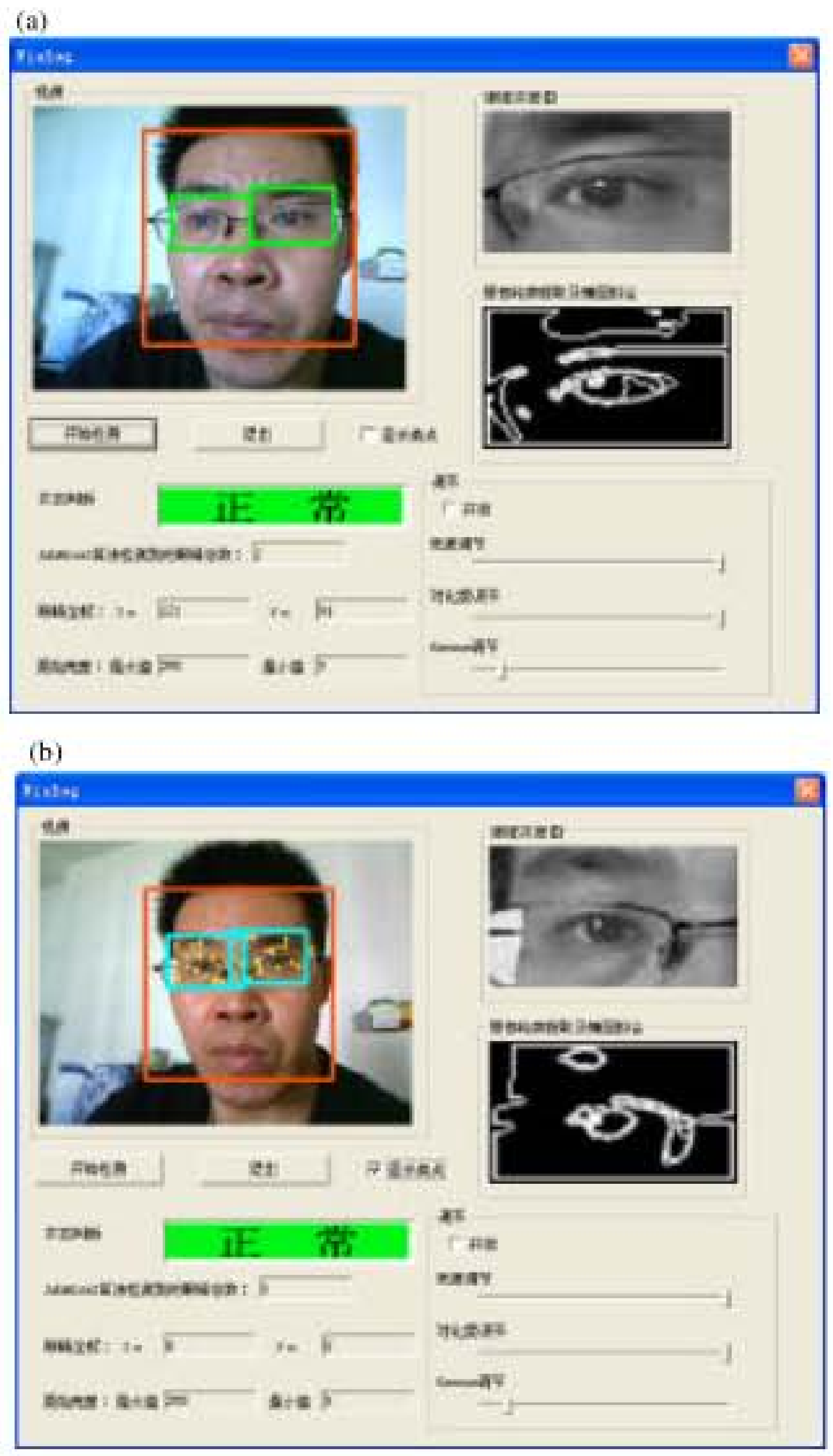

Fig. 10: The recognition result based on the K-L algorithm and Adaboost cascade classifiers

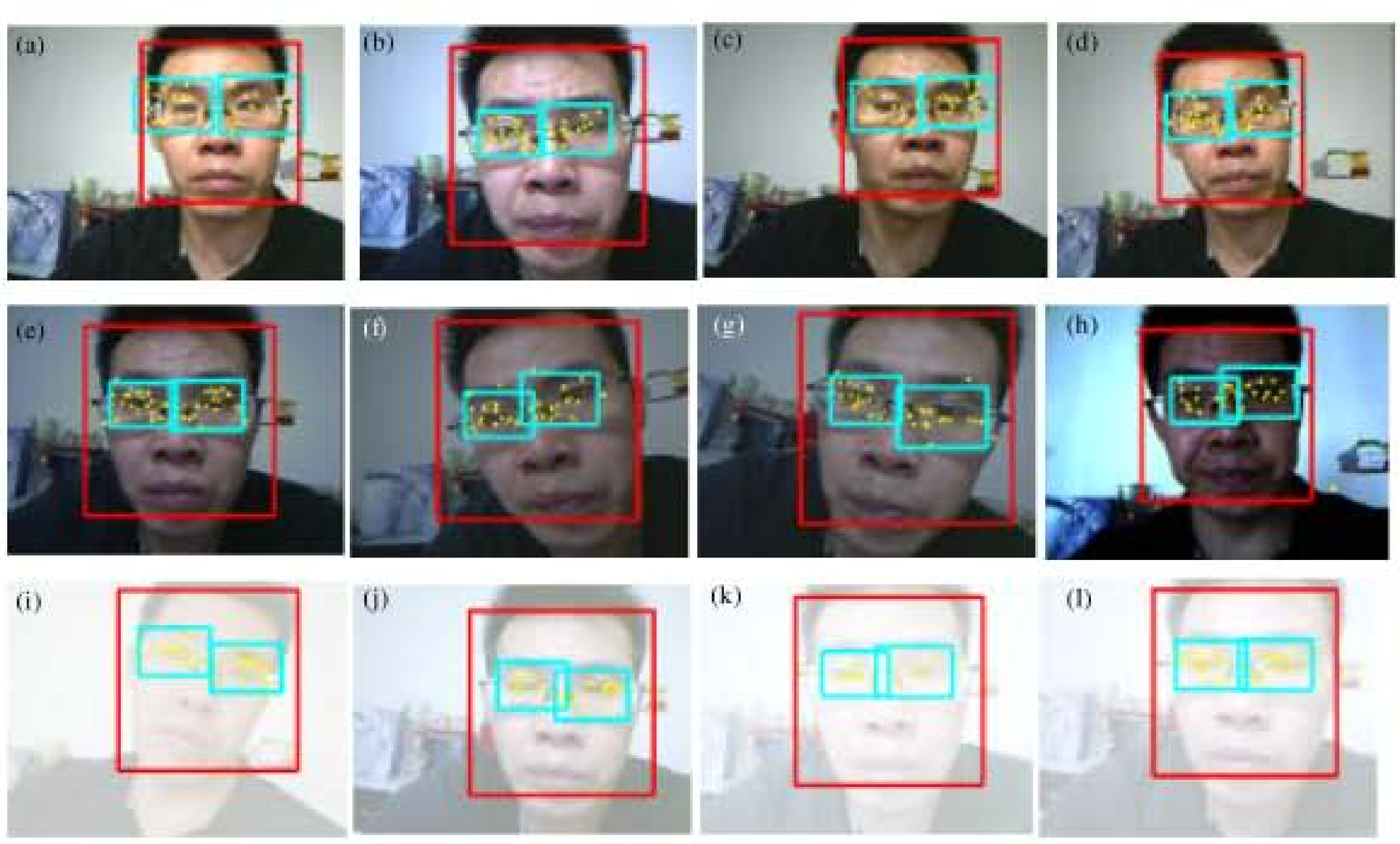

Fig. 11: The tracking result of the K-L algorithm

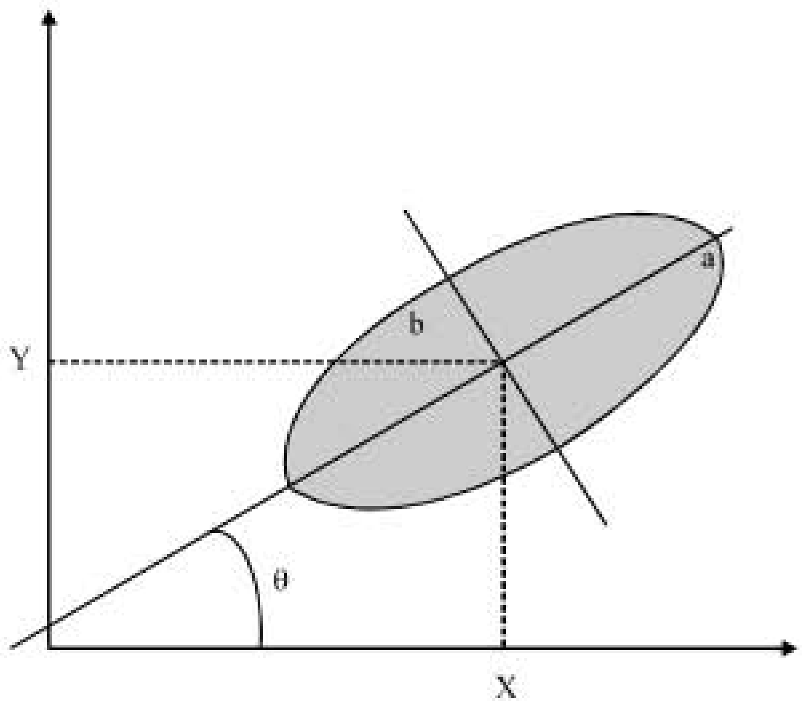

Fig. 12: The geometric feature of ellipse

As the Fig. 15-17 is showed, the three states of the eye have been determined by the contour recognition of the eye. The real time ability is also be considered beside the reliability for the recognition. Because the hard system is composed of the camera of usb interface and the laptop, the data transformation exerts some influence on the recognition rate of the eye. Now the system is at the speed of 16 frames/second. The recognition rate will be high when the eyes location is stable and the feedback of early warning is able to be received on time. However, if the hardware system used the camera with COM interface and embedding CPU with Coronal, the processing speed would be improved to 120 frames/ second in the both directions and the real time ability of eye recognition would be proposed tremendously.

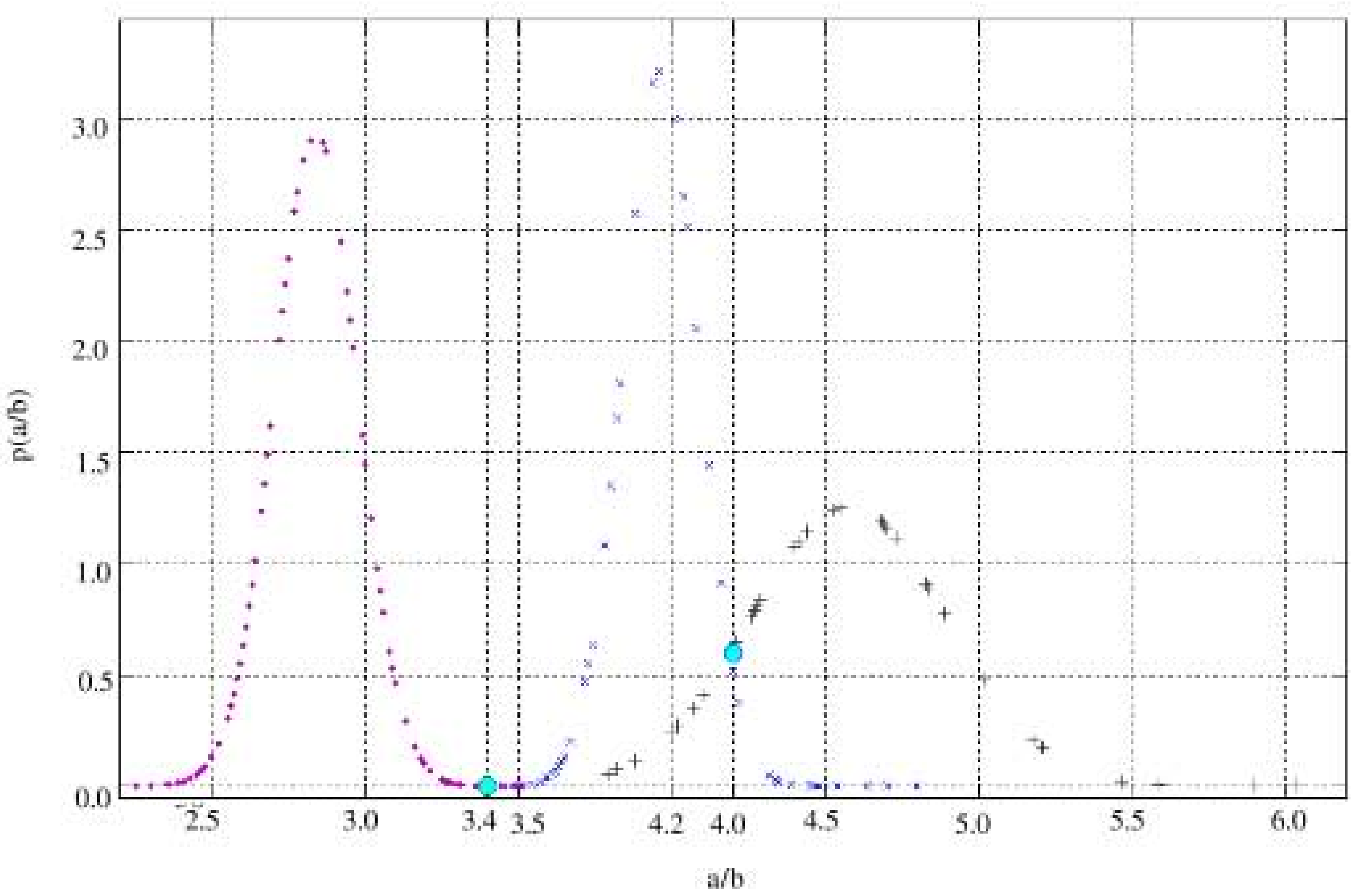

Fig. 13: The distribution curve of a/b of different eye states

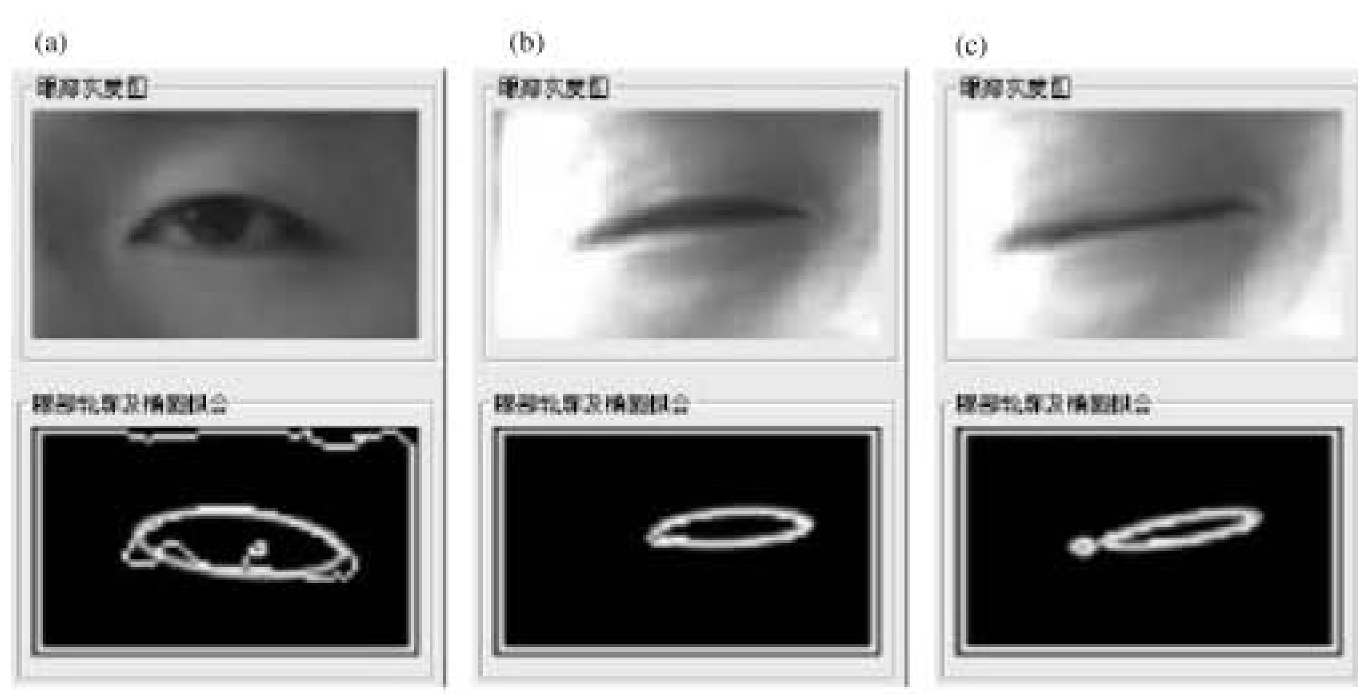

Fig. 14: The result of the eye state judgment. (a) Normal state (b) fatigue state and (c) close state

Fig. 15: The eye detection experiment results of normal driving state

Fig. 16: The eye detection experiment results of fatigue driving state

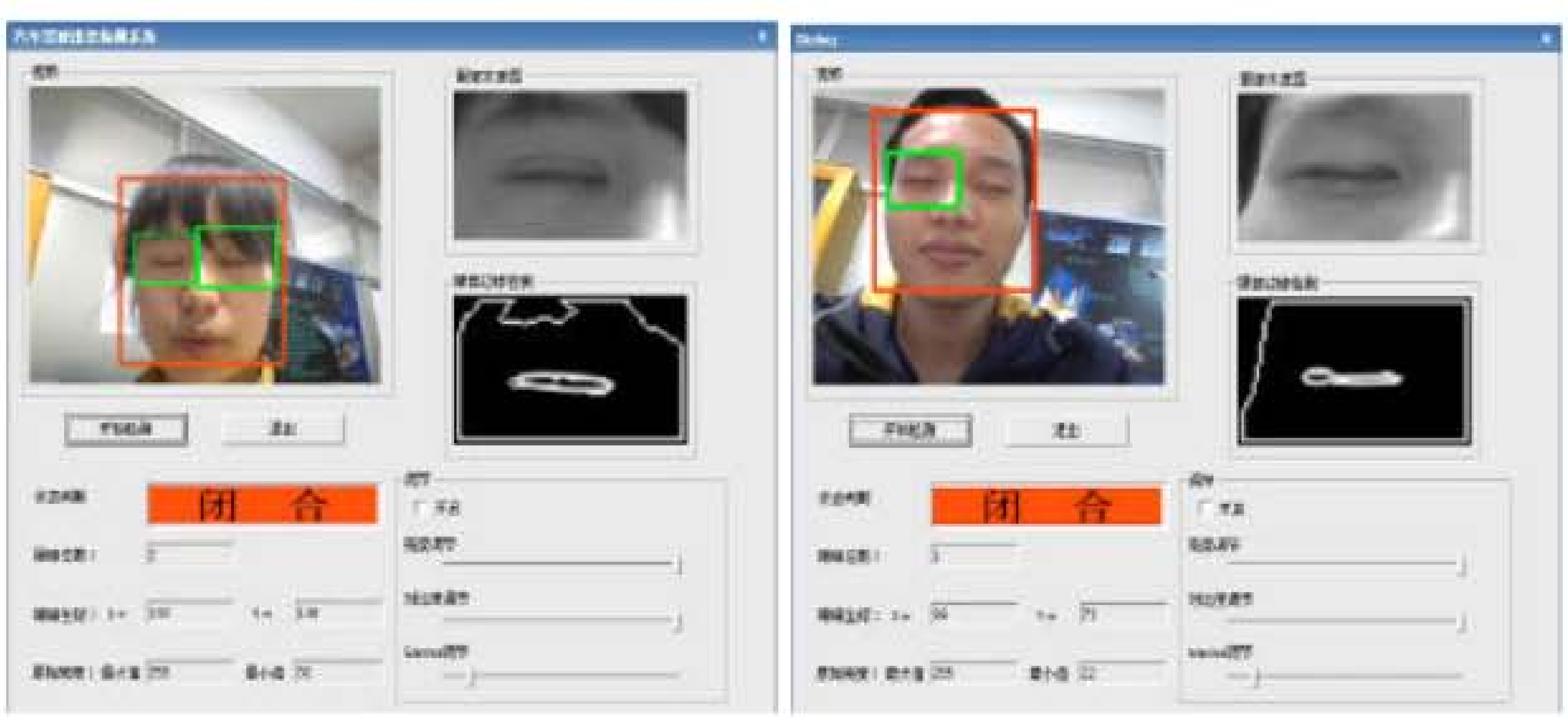

Fig. 17: The eye detection experiment results of eye-closed driving state

CONCLUSION

In this study K-L algorithm is used to track the eye, which has been recognized by Adaboost algorithm. Then those non-eyes areas are excluded by the set threshold, further Freeman chain code is taken to pick up the contour of binary image. Finally, the contour of binary image is fitted using the least square method so that the fatigue state of the eye is determined.

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