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Real-time Eye Locating and Tracking for Driver Fatigue Detection

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Abstract. Assistant driving systems have attracted more and more attention during recent years. Among them fatigue detection plays a key role because of its close relationship with accidents. In this paper, we propose a novel method which uses eye locating and tracking technique to detect driver fatigue. The present method consists of four steps. First, we employ Adaboost and Haar-like features to construct a robust classifier which can detect eye corner points. Second, we use extended parabolic Hough transformation to construct the parabola curves of upper and lower eyelid. Then, particle filter algorithm is used to track eye corner points in video sequences. Finally, the driver fatigue state is estimated through computing the frequency of eye opening and closing intervals. Experimental results from real environment datasets are given in our discussion as well.

I. Introduction

When more and more vehicles appear on the road, traffic congestion, accidents and other problems make Intelligent Transportation Systems (ITS) much more important since its application in guaranteeing safer driving. In ITS, driver reliability plays an important role. Statistics of traffic accidents show that driver fatigue is a primary cause of accidents, especially for long-haul driving [1]. According to statistics given by the National Highway Traffic Safety Administration, there are about 100,000 accidents caused by drowsy drivers, which result in more than 1,500 fatalities and 71,000 injuries every year in the United States [2]. Statistics also show that 7% of crashes of and 40% of fatal accidents are due to driver fatigue. The same thing happens in Europe. For example, Germany Insurance Agent Association estimates that 25% of fatalities are due to driver fatigue. For this reason, the issue of driver fatigue detection has attracted more and more attention from researchers and engineers in the world.

In relevant areas, there have already existed many methods to detect driver fatigue. Some detection techniques are based on physiological phenomena like brain waves, heart rate, pulse rate and respiration. These techniques are intrusive, since they need to attach some electrodes to drivers. Other methods are to monitor the transportation hardware system status, such as lane deviation, steering wheel movements and acceleration, braking, gear changing, etc., these methods are subject to several limitations such as vehicle types, driver's experiences, geometric characteristics and states of the road [3]. As human eyes express the most direct reaction when dozing or sleeping, eye blink detection has been widely used as the basis for the driver fatigue detection by researchers. In this paper, we detect the drivers' fatigue by analyzing the state of eyes. More specifically, locating and tracking algorithms are chosen to deal with the problem.

This paper is organized as follows. After this short introduction, we will simply review some previous work on the driver fatigue detection problem. Then, we focus our discussion on the eye locating method. The eye tracking algorithm is described in fourth part. Experimental results obtained from this computation are given in fifth part. The conclusion is given in last part.

II. Related Work

Generally, fatigue will result in noticeable decline in the driver's ability of perception, recognition, and vehicle control, and even lead to fatal traffic accidents. Much work has been done in the investigation of driver fatigue phenomenon and in the development of driver fatigue detection technology. Among the work, vision-based eye state detection method is one of the most important branches, because in transportation systems, almost 90% of information used by drivers is visual [4]. Hence, technologies that measure eye closure, eye movements or ocular physiology, appear to be very suitable choices to monitor driver fatigue.

PERCLOS (Percent Eye Closure) methodology, a video-based method that measures eye closure, is a reliable and effective determination of a driver's alertness level. To obtain PERCLOS, we should extract the distance between eyelids exactly. Several methods for eyelid detection have been proposed. Sun et al. [5] introduced a simplified alignment step for Active Shape Model method and applied it to extract eyelid contour. However, their methods mainly focused on eyelid detection for open eyes. Wu et al. [6] used deformable templates to extract eye contour. To avoid unexpected shrinking, new energy terms were imposed to limit the eye template length. Color information was also used to segment eye region therefore their method only performed well for color images.

Besides, eyelid tracking also got researchers' attention. Tian et al. [7] combined feature point tracking and masked edge filtering techniques to track eyes. Deformable templates for open and closed eyes were applied to describe eye contour change. Tan and Zhang [8] modified Tian's approach by amending the energy function and applying AR models to predict the eyelid patterns. Good performances were obtained but high quality images were also required.

III. Eye Locating

A. Eye Corner Points Detection Using Adaboost and Haar-like Features

The first step of our method is to detect corner points of two eyes. Because follow-up tasks are all based on the result of this step, it is very important to adopt a good algorithm which can detect corner points robustly, efficiently and rapidly. In our system, we use Adaboost and Haar-like features to create a classifier to do the job. Experimental results show it can finish the detection work very well.

Since Viola and Jones use Adaboost successfully in their face detection system [9], the Adaboost method has already become one of the most popular methods in object detection systems. Adaboost will train a small number of weak classifiers, and each weak classifier selects a Haar-like feature from the numerous features. The final classifier is a cascade of these weak classifiers.

Haar-like features are widely used because they can effectively capture different image details and fast algorithms using integral images to calculate such features are very quickly. Fig.1 shows all Haar-like features we used. In addition to the basic Haar-like features proposed by Viola (mode 0), Lienhart [10] add some other similar features to extend the Haar-like feature sets (mode 1 and mode 2). Fig.2 shows some positive and negative samples used in our training process.

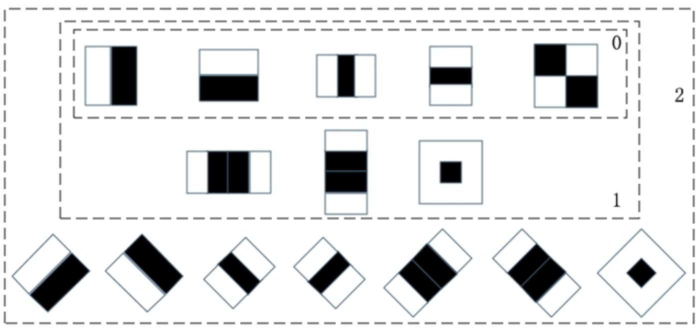


Fig.1 Haar-like Feature Sets

Fig.2 Training Samples

After we get the classifier, it will be applied with eye images to obtain eye corner points (methods of face detection and eye extraction are not discussed in this paper). Some results are shown in Fig.3.

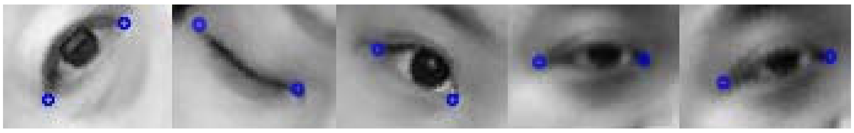


Fig.3 Results of Eye Corner Points Detection

B. Eye Contour Detection Using Extended Parabolic Hough Transformation

When we get the corner points of one eye, an extended Parabolic Hough transformation would be used to obtain the contour information of the eye (see Fig.4).

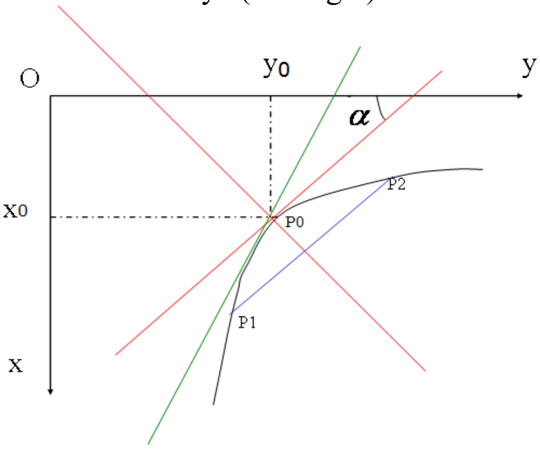


Fig.4 Diagram of Extended Parabolic Hough Transformation

Given two symmetrical points $P_1(x_1, y_1)$, $P_2(x_2, y_2)$ on the parabola, vertex of the parabola must be at the midperpendicular $\overline{P_1P_2}$. Assuming the inclination angle of parabola is α, then:

$$\begin{cases} \cos\alpha = \dfrac{x_2 - x_1}{\sqrt{(x_2-x_1)^2 + (y_2-y_1)^2}} \\ \sin\alpha = -\dfrac{y_2 - y_1}{\sqrt{(x_2-x_1)^2 + (y_2-y_1)^2}} \end{cases} \tag{1}$$

From the straight line equation of $\overline{P_1P_2}$:

$$\sin\alpha \bullet \left(x - \frac{x_1 + x_2}{2}\right) + \cos\alpha \bullet \left(y - \frac{y_1 + y_2}{2}\right) = 0$$

We can get the equation of midperpendicular:

$$\cos\alpha \bullet \left(x - \frac{x_1 + x_2}{2}\right) - \sin\alpha \bullet \left(y - \frac{y_1 + y_2}{2}\right) = 0$$

So the $P_0(x_0, y_0)$ should satisfy:

$$\cos\alpha \bullet \left(x_0 - \frac{x_1 + x_2}{2}\right) - \sin\alpha \bullet \left(y_0 - \frac{y_1 + y_2}{2}\right) = 0 \tag{2}$$

Then the equation of the parabola can be expressed as:

$$\left[\cos\alpha \bullet (x - x_0) - \sin\alpha \bullet (y - y_0)\right] = a\left[\cos\alpha \bullet (y - y_0) + \sin\alpha \bullet (x - x_0)\right]^2 \tag{3}$$

Where a is the quadratic coefficient of parabola. Therefore we can get the Hough transformation of parabola when symmetrical points are provided. Firstly $\cos\alpha, \sin\alpha$ can be computed. Provided x_0

as independent variable, we can compute y_0 by Eq.2. Then setting two dimension accumulator array $A(a, x_0)$ and obtain a according to edge points using Eq.3. After traveral of all edge points, we can get the coordinate corresponding to the extremum of accumulator array, which is a, x_0. Then y_0 can be computed using Eq. 2 and all coefficients of parabola are obtained.

Given eye corner points, we can obtain the upper and lower eyelid information through combining edge detection with extended parabolic Hough transformation mentioned above. Some results are shown in Fig. 5.

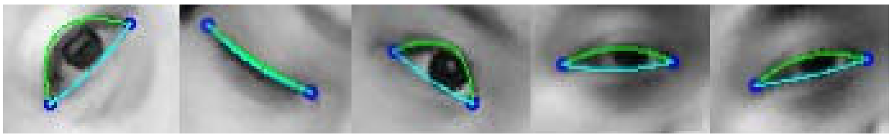


Fig.5 Detection Results of Extended Parabolic Hough Transformation

IV. Eye Tracking

Using the eye corner points detection method mentioned above, we can get 4 key corner points of two eyes. Their coordinates construct the state vector of particles as follows:

$$X = (x_1, y_1, x_2, y_2, \cdots, x_4, y_4)$$

If each state vector is allowed change freely, an eight-dimension state vector will need lots of particles which may affect the calculating speed, so we must find other lower dimension model to substitute. Considering the position change of key points doesn't satisfy rigid motion when face pose changes, so we use shape model method coming from ASM algorithm [11]. First, according to given key points, central point, scale and rotation are normalized. Second, mean value $\bar{x}$ and column vector of PCA first dimension are computed. Then key points in a single image can be expressed as:

$$X = T_{(s,\theta,t_x,t_y,c)}(\bar{x} + c \cdot u) \tag{4}$$

Where s is scale value, θ is angle value, (t_x, t_y) represents the change of displacement and c is the variation factor of first item. Let $a = s \bullet \cos\theta, b = s \bullet \sin\theta$, then:

$$X = T_{(a,b,t_x,t_y,c)}(\bar{x} + c \cdot u) \tag{5}$$

Since c is determined by person identity and can be obtained in the initial frame by detection methods, we can get state vector $Y = (a, b, t_x, t_y)$. According to the statistics of key points changing in video imags, we found there is no obvious relationship between the (t_y, a, b) and the changing direction of face pose, so the variation can be seen as random movement which satisfy the mixture Gaussian model. Let $\Delta Y = (\Delta a, \Delta b, \Delta t_x, \Delta t_y)$, then:

$$\begin{gathered} \Delta a \sim \mathcal{N}(0, \sigma_{\Delta a}) \quad \Delta b \sim \mathcal{N}(0, \sigma_{\Delta b}) \quad \Delta t_y \sim \mathcal{N}(0, \sigma_{\Delta t_y}) \\ \Delta t_x \sim p_1 \bullet \mathcal{N}(0, \sigma_{\Delta t_x}) + p_2 \bullet \mathcal{N}(-u, \sigma_{\Delta t_x}) + p_3 \bullet \mathcal{N}(u, \sigma_{\Delta t_x}) \end{gathered} \tag{6}$$

The dynamic model is $P(Y_t \mid Y_{t-1}) = Y_{t-1} + \Delta Y$.

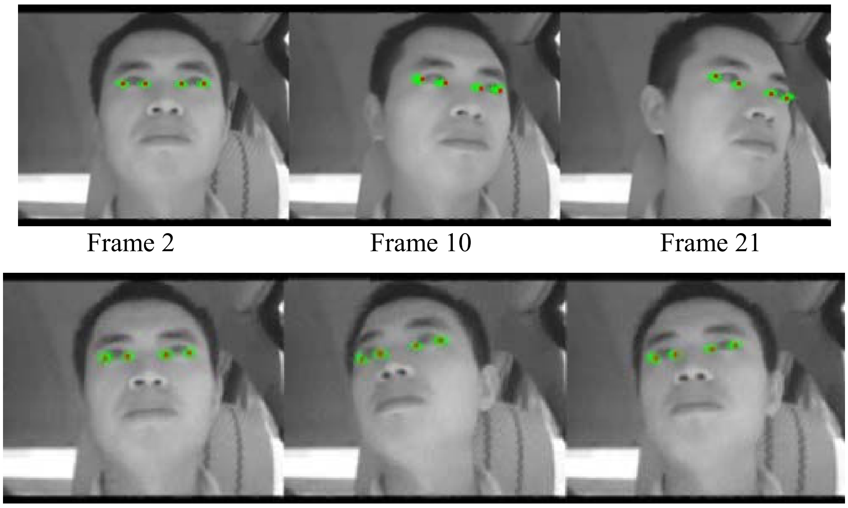
Here we use the detected eye corner points mentioned above. For the n-th point, the position of detected corner feature point is assumed as $w_i^n = (x_i^n, y_i^n), i = 1, \cdots, S$, in which S is the numbers of detected corner points. Let w^n present the position of one key point determined by Y_t:

$$P(w^n \mid Y, Z) \propto 1 + \frac{1}{\sqrt{2\pi}\sigma\alpha} \sum_i \exp\left(-\frac{\left\| w^n - w_i^n \right\|^2}{2\sigma^2} \right) \tag{7}$$

The integral posterior probability is

$$P(W \mid Y,Z) = P\left(w^1, w^2, w^3, w^4 \mid Y\right) = \prod_{n=1}^{4} P\left(w^n \mid Y,Z\right) \tag{8}$$

Some tracking results in a real environment video sequence are given in Fig. 6 (corner points in first frame are obtained by algorithm mentioned above). Where green points represent the position of particles and red points represent the last estimated results of key points.



Frame 2 Frame 10 Frame 21

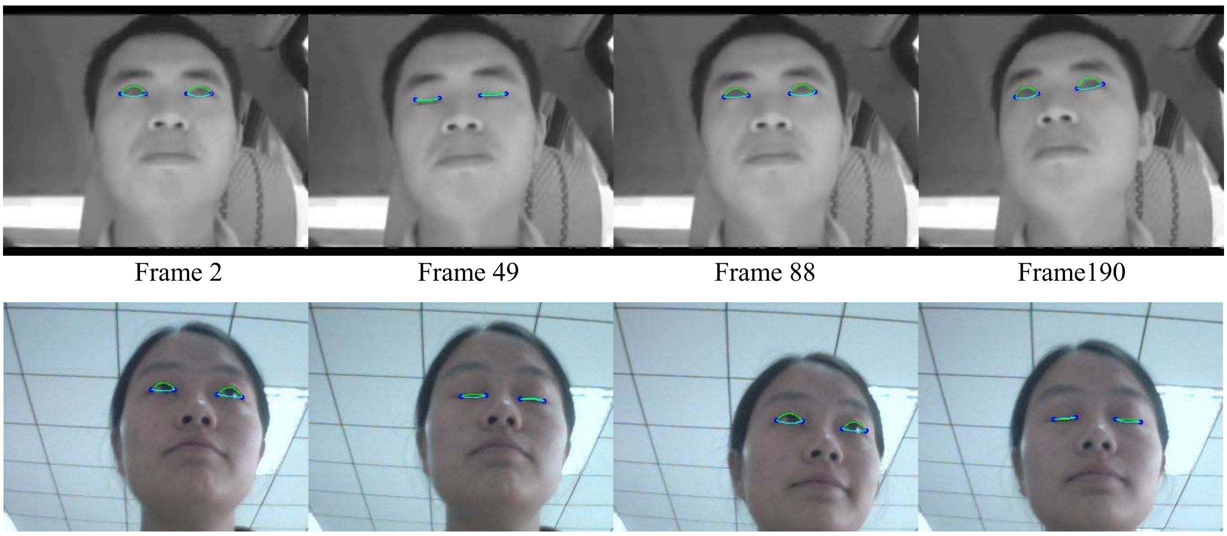
Frame 88 Frame 168 Frame 190

Fig.6 Results of Eye Corner Points Tracking

Assuming X is the tracking result of all key points in a image, then $X = (x_1, y_1, x_2, y_2, \cdots, x_4, y_4)$, X_S is the result marked manually. The calculation error $\varepsilon = \| X - X_S \|_2$ and error changing curve is drawn in Fig. 8 (We can see from the diagram that the tracking error is less than 3 pixels):

V. Experimental Results

Up to now, we have already obtained the complete and precise eyes' information of the driver in each frame, then PERCLOS can be easily obtained from the changes of the distance between eyelids over time and fatigue or blink state can be recognized. Some results on two different video sequences are shown in Fig. 7. Fatigue and blink detection result is drawn in Fig. 9.



Frame 2 Frame 49 Frame 88 Frame190

Frame 6 Frame 35 Frame 103 Frame 151

Fig.7 Final Results of Our Method on Different Video Sequences

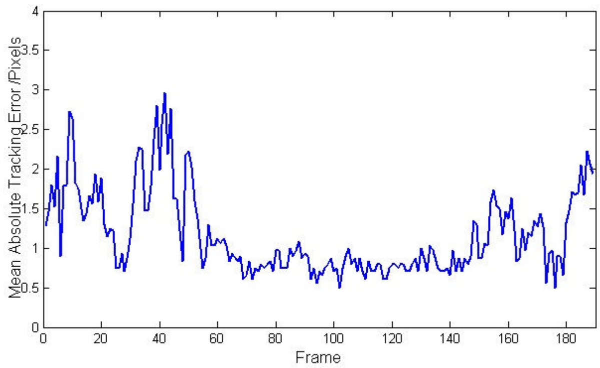


Fig.8 Error Curve of Eye Points Tracking

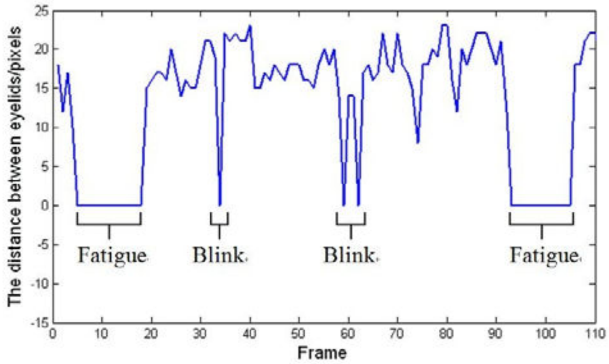


Fig.9 Fatigue and Blink Detection

VI. Conclusions

In this paper, a method for driver fatigue detection is proposed. The algorithm is capable of detecting and tracking driver's eye corner points in real time. It is robust enough to efficiently obtain driver fatigue state in different environment and not affected by changing of eyes color, eyes shape, and eyes size. Promising experimental results showed that our method performs well both on real vehicle videos and in-lab videos.

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References

[1] S. G. Klauer, T. A. Dingus, V. L. Neale. The Effects of Fatigue on Driver Performance for Single and Team Long-Haul Truck Drivers. In: 2nd International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design. 143-147, (2003).
[2] Q. Ji, Z. Zhu, P. Lan. Real-Time Nonintrusive Monitoring and Prediction of Driver Fatigue. IEEE Transactions on Vehicular Technology. 2004, 53(4): 1052-1068.
[3] H. Ueno, M. Kaneda, M. Tsukino. Development of Drowsiness Detection System. In: Proceedings of Vehicle Navigation and Information Systems Conference. 15-20, (1994).
[4] R. R.Knipling, J. S.Wang, and J. N.Kanianthra. Current NHTSA drowsy driver R&D. In: Fifteenth International Technical Conference on the Enhanced Safety of Vehicles. Vol.1. (1996).
[5] K. Sun and H. Wang, A composite Method to Extract Eye Contour. In: First International Conference on Affective Computing and Intelligent Integration, 535-541, (2005).
[6] Y. Wu, H. Liu, H. Zha. A New Method of Detecting Human Eyelids Based On Deformable Templates. In: International Conference on Systems, Man and Cybernetics. 604-609, (2004).
[7] Y. Tian, T. Kanade, J. F. Cohn. Dual-State Parametric Eye Tracking. In: Proceedings of International Conference on Automatic Face and Gesture Recognition. 110-115, (2000).
[8] H. Tan, Y. Zhang. Detecting Eye Blink States by Tracking Iris and Eyelids. Pattern Recognition Letters. 2006, 27(6): 667-675.
[9] P. Viola, M. Jones. Rapid Object Detection Using a Boosted Cascade of Simple Features. In: Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 511-518, (2001).
[10] R.Lienhart and J. Maydt. An Extended Set of Haar-like Features for Rapid Object Detection. In: Proceedings of International Conference on Image Processing. 900-903, (2002).
[11] T. F. Cootes, C. J. Taylor. Statistical Models of Appearance for Medical Image Analysis and Computer Vision. SPIE, 2001: 4322, 236-248.

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DOI References

[2] Q. Ji, Z. Zhu, P. Lan. Real-Time Nonintrusive Monitoring and Prediction of Driver Fatigue. IEEE Transactions on Vehicular Technology. 2004, 53(4): 1052-1068.
doi:10.1109/TVT.2004.830974
[8] H. Tan, Y. Zhang. Detecting Eye Blink States by Tracking Iris and Eyelids. Pattern Recognition Letters. 2006, 27(6): 667-675.
doi:10.1016/j.patrec.2005.10.005
[11] T. F. Cootes, C. J. Taylor. Statistical Models of Appearance for Medical Image Analysis and Computer Vision. SPIE, 2001: 4322, 236-248.
doi:10.1117/12.431093
[2] Q. Ji, Z. Zhu, P. Lan. Real-Time Nonintrusive Monitoring and Prediction of Driver Fatigue. EEE Transactions on Vehicular Technology. 2004, 53(4): 1052-1068.
doi:10.1109/TVT.2004.830974
[8] H. Tan, Y. Zhang. Detecting Eye Blink States by Tracking Iris and Eyelids. Pattern Recognition etters. 2006, 27(6): 667-675.
doi:10.1016/j.patrec.2005.10.005