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A new real-time eye tracking based on nonlinear unscented Kalman filter for monitoring driver fatigue

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Abstract: A new scheme for driver fatigue detection is presented, which is based on the nonlinear unscented Kalman filter and eye tracking. Assuming a probability distribution than to approximate an arbitrary nonlinear function or transformation, eye nonlinear tracking can be achieved using an unscented transformation (UT), which adopts a set of deterministic sigma points to match the posterior probability density function of the eye movement. Driver fatigue can be detected using the percentage of eye closure (PERCLOS) framework in a realistic driving condition after the eye nonlinear tracking. This system was tested adequately in realistic driving environments with subjects of different genders, with/without glasses, in day/night driving, being commercial/noncommercial drivers, in continuous driving time, and under different road conditions. The last experimental results show that the proposed method not only improves the robustness for nonlinear eye tracking, but also can provide more accurate estimation than the traditional Kalman filter.

Keywords: Eye tracking; Unscented Kalman filter (UKF); Fatigue detection; PERCLOS

1 Introduction

Driver fatigue is one of the important factors that cause traffic accidents, and the ever-increasing number of accidents due to a diminished driver's vigilance level has become a problem of serious concern to the society. Drivers with a diminished vigilance level suffer from a marked decline in their abilities of perception, recognition, and vehicle control, which poses serious danger to their own life and the lives of other people [1, 2]. The National Police Administration in France concludes that 14.9 percent of accidents causing human hurt and 20.6 percent of accidents causing death are fatigue-related [3]. Statistics show that a leading cause of fatal or injury-causing traffic accidents is driver fatigue. With the ever-growing traffic conditions, this problem will further increase. Therefore, how to avoid fatigue driving efficiently can help prevent many accidents, consequently save money and reduce personal suffering. For this reason, developing driver fatigue detection systems and related intelligent safety applications is very important to vehicular systems in the future.

In the past ten years, many countries all over the world have begun to pay attention to the driver safety problem and to investigate the driver's mental states relating to driving safety. And some driver fatigue detection methods have been proposed which can detect whether the driver is tired, such as drowsiness or inattention, for generating some warning alarms to alert the driver [1∼8]. Despite the success of the existing approaches/systems for extracting characteristics of a driver using computer vision technologies, and other current efforts in this area, it is a challenging issue due to a variety of factors. The one main reason is the variety of eyes moving speed, external illumination interference and realistic lighting conditions. So nonintrusive eye tracking is a very difficult work in driving environments. Another main reason is that it is very difficult to model the driver's eye movement dynamics because of the eye motion being the high nonlinearity. In references [3, 7], Qiang Ji et al. have also made significant improvements of facial fatigue detection over existing techniques. However, their methods need infrared (IR) eye detector, or bright pupils and steady illumination. Their eye-tracking method that used Kalman filtering is a linear system estimation algorithm. In fatigue detection system, the eye motion has the high nonlinearity of the likelihood model that the standard Kalman filter is no longer optimal in realistic driving environments.

To tackle some of those problems, we propose a new real-time eye tracking based on a nonlinear unscented Kalman filter for diver fatigue detection. Eye nonlinear tracking can be achieved using unscented transformation. From the theoretical analysis, the unscented Kalman filter avoids the use of Jacobian matrices, which simplifies the implementation of the filter and potentially reduces its complexity. Moreover, the unscented Kalman filter also provides a more accurate estimation result and reduces the potential instability issues that can arise from the Kalman filter when the linearization is not a good approximation. Driver fatigue can be detected using calculated PERCLOS under realistic driving conditions after the eye nonlinear tracking. This system was validated under real-life fatigue conditions, and it was found to be reasonably robust, reliable, and accurate in fatigue characterization.

The organization of the paper is as follows. Kalman filtering-based fatigue detection system related research is briefly given in the next section. Section 3 gives the pro-

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posed driver fatigue detection system. The performance evaluation for driver fatigue detection is shown in Section 4. Finally, conclusion is in Section 5.

2 Kalman filtering-based fatigue detection system

In [3, 7], the authors have made significant improvements of facial fatigue detection using the Kalman filtering tracking algorithm. They proposed a fatigue detection system based on a combination of a Kalman filtering tracking algorithm and the bright pupil effect due to an active IR illumination. Their eye-tracking method consists of two major modules. The first tracking module is a Kalman filter-based bright pupil tracking, augmented with a support vector machine (SVM) classifier for pupil verification. If the first eye-tracking module fails, then the authors will activate the second module based on the mean shift tracking [9] to continue eye tracking. And two modules alternate during tracking to complement each other. The Kalman filtering-based fatigue detection system is briefly discussed below.

2.1 System model

The system in [3, 7] developed the fatigue detection system by combining a Kalman filter eye tracker with the mean shift eye tracker. The flow chart of the Kalman filtering-based fatigue detection system is depicted in Fig.1. The authors build a special IR illuminator that illuminates a person's face and use an IR-sensitive camera to acquire an image. After locating the eyes in the initial frames, the Kalman filtering is activated to track bright pupils [3, 7]. If it fails in a frame due to disappearance of bright pupils, eye tracking based on mean shift will take over. These two-stage eye trackers work together, and they complement each other.

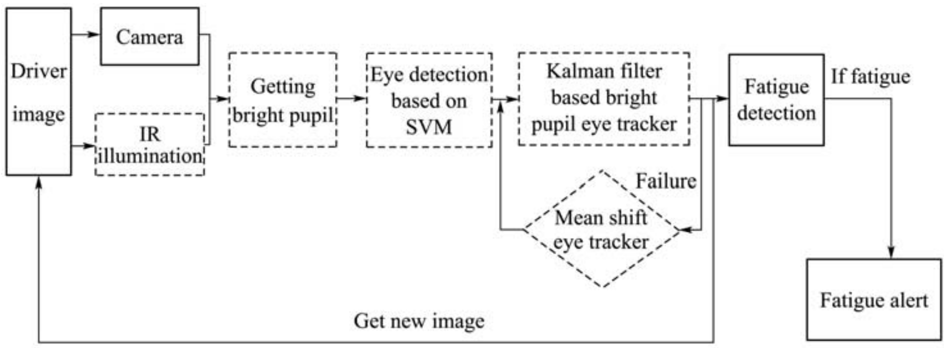


Fig. 1 Flow chart of the Kalman filtering-based fatigue detection system.

2.2 Eye tracking with Kalman filtering

In [3, 7], the motion of a pupil at each instant can be characterized by its position and velocity. Let (c_t, r_t) parameters be the horizontal and vertical positions of the pupil measured in pixels and (u_t, v_t) be the horizontal and vertical components of the pupil's velocity measured in deg/s. The state vector at time t can be represented as $x_t = (c_t \ \ r_t \ \ u_t \ \ v_t)^t$. The system can therefore be modeled as

$$X_{t+1} = \Phi X_t + w_t, \tag{1}$$

where w_t represents system perturbation.

The authors [3, 7] further assumed that a fast feature extractor estimates $z_t = (\hat{c}_t, \hat{r}_t)$ as the pupil position at time t. Therefore, the measurement model in the form needed by the Kalman filter is

$$z_t = HX_t + v_t, \tag{2}$$

where v_t represents measurement uncertainty. Specifically, the position of current frame t is estimated based on a simple local threshold in the neighborhood of the predicted position, assuming the existence of the bright pupil effect. Given the state model in equation (1) and the measurement model in equation (2) as well as some initial conditions, the state vector X_{t+1}, along with its covariance matrix $\sum_{t+1}$, can be updated using the system model and the measurement model.

2.3 Mean shift eye tracking

The mean shift tracking algorithm is an appearance-based tracking method, and it employs the mean shift iterations to find the target candidate that is the most similar to a given model in terms of intensity distribution, with the similarity of the two distributions being expressed by a metric based on the Bhattacharyya coefficient. The derivation of the Bhattacharyya coefficient from sample data involves the estimation of the target density q and the candidate density p, for which the authors employ the histogram formulation. At location y, the sample estimate of the Bhattacharyya coefficient for target density q and target candidate density $p(y)$ is given by

$$\hat{\rho}(y) \equiv \rho[\hat{p}(y), \hat{q}] = \sum_{u-1}^{m} \sqrt{\hat{p}_u \hat{q}_u}, \tag{3}$$

where m is the quantization level for histograms p and q. The distance between two distributions can be defined as

$$d(y) = \sqrt{1 - \rho[\hat{p}(y), \hat{q}]}. \tag{4}$$

To reliably characterize the intensity distribution of eyes and noneyes, the intensity distribution is characterized by two images: even and odd fields, resulted from deinterlacing the original input images. They are under different illuminations, with one producing dark pupils and the other bright pupils in [9].

During eye tracking, the authors update the target eye model whenever the bright pupil tracker tracks the eyes successfully in order to reduce the error propagation, resulted from the mean shift drifting. The Kalman filter-based bright pupil tracking and mean shifting tracking alternate during driver fatigue detection. For detailed discussion, please refer to [3, 7].

3 The proposed driver fatigue detection system

The system in [3, 7] requires bright pupil-based IR illumination; this will tend to limit the scope of the method. The Kalman filtering algorithm is a good linear system estimation algorithm under simple background and Gaussian distribution. In driver fatigue detection, the system dynamics or observation models are often nonlinear. So the standard Kalman filter is no longer optimal in realistic driving environments. In this paper, we present a new driver fatigue detection based on nonlinear unscented Kalman filter and eye tracking. The detailed steps are described in the following subsections.

3.1 System model

The proposed driver fatigue detection system model is shown in Fig. 2. First, we locate the driver's face using Haar algorithm, and reduce the detecting eyes range for improving the tracking veracity and speed. Second, the geometric properties and projection technique are used for eye location. Third, the UKF is used for real-time eye-tracking method because UKF is of good tracking performance for quick moving target. The last experimental results show improvement of our method over the existing system in [3, 7].

3.2 Face detection

When an automobile is running on the road, it is very difficult to automatically locate or detect the driver's eyes for capturing images due to complex background and changes in high-speed moving. So we must firstly find the location of the face and reduce the detecting eyes range for improving the tracking veracity and speed, reducing the affect of the background. Recently, some effective and efficient human face detection techniques have been proposed in [4, 6]. In this paper, we locate the driver's face using the Haar algorithm. For detailed Haar algorithm, refer to [10, 11].

3.3 Eye detection

Investigative report concludes that the driver has rapid eyes movement and low head rotation [3]. And we know that drivers often pay attention to front and surrounding objects when driving. According to the normal position of the eyes in the driver's face, it is reasonable to assume that the possible location of eyes will be in the block of the upper three fifths of the driver face region, as shown in Fig.3 (a). After defining the eye region, we can use geometric properties and projection technique for eye detection. Because the pixels of the eye region are relatively lower than other regions, we can calculate the pixel value for eye detection. Performing horizontal and vertical projections on the eye region map, the exact position of the eye can be located at the peak, as shown in Fig.3 (c) and (d). Two peaks in Fig.3 (c) show the horizontal location of eyes. The peak in Fig.3 (d) is the vertical location of eyes; and the second peak value is the vertical projection of eyebrows. After locating the left and right eye positions, we use a bounding box for the connected component on the original image to enclose the eye image, which is used as the template for eye tracking by the unscented Kalman filter in the next frame, as shown in Fig.3 (e)∼(g).

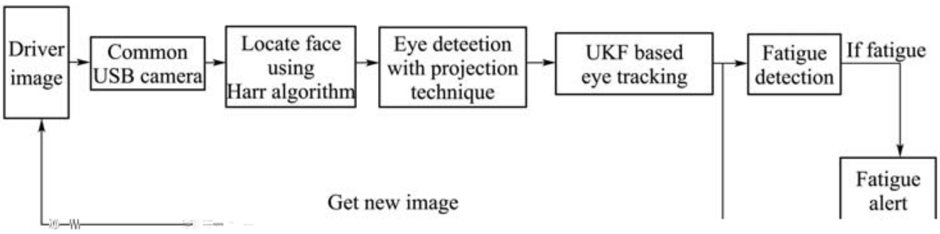


Fig. 2 Flow chart of the unscented Kalman filter-based fatigue detection system.

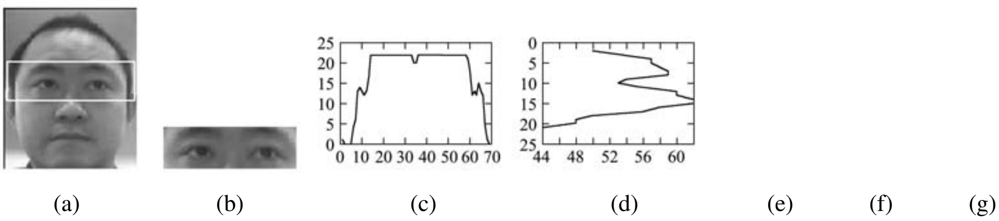


Fig. 3 Result of eye detection.

3.4 UKF filter-based eye tracking

In fact, the driver has low head rotation when he watches the rearview mirror, and the driver's eyes turn left and right promptly. So we might focus on the characters of the driver's eye motion because the eyes have very quick response to the driving environments. Eye blinking is usually used by researchers as the basis for driver fatigue detection. In [3, 7], the authors proposed a real-time eye-tracking method to detect driver fatigue, which is combined with a Kalman filtering algorithm and mean shift based on IR illumination. However, it utilized the special bright pupil effect under IR to detect and track eyes, and the Kalman filtering is a good linear estimation algorithm in simple background and Gaussian distributions. Unfortunately, realistic driving environments are very complex, and the system dynamics or observation models are often nonlinear, such as the conversion from spherical to Cartesian co-ordinates in the eye-tracking system. So the standard Kalman filter is no longer optimal in realistic driving environments.

The unscented Kalman filter proposed by Julier and Uhlmann [12, 13] not only can avoid the use of Jacobian matrices, simplifying the implementation of the filter and potentially reducing its complexity, but also provides more accurate estimation results, reducing the potential instability issues that could arise from the Kalman filter when the linearization is not a good approximation. To accurately track eye motions in realistic driving environments, this paper uses a UKF algorithm for eyes quick motion tracking without bright pupil and IR illumination.

The real-time eye tracking using the UKF algorithm is described as follows:

1) Initialization:

$$\hat{x} = E[x_0], \ \ P_0 = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^{\mathrm{T}}], \tag{5}$$

where $\hat{x}$ and P_0 are the initializations of state vector and covariance.

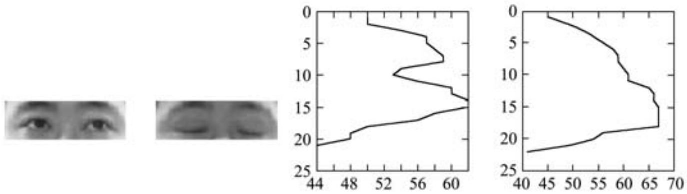
Augmented stated vectors:

$$\hat{\mathcal{X}}_0^{\alpha} = E[x^{\alpha}] = [\hat{x}_0^{\mathrm{T}} \ \ 0 \ \ 0]^{\mathrm{T}}, \tag{6}$$

$$P_0^{\alpha} = E[(x_0^{\alpha} - \hat{x}_0^{\alpha})(x_0^{\alpha} - \hat{x}_0^{\alpha})^{\mathrm{T}}] = \begin{bmatrix} P_0 & 0 & 0 \\ 0 & R^v & 0 \\ 0 & 0 & R \end{bmatrix}$$

(a) (b) (c) (d) (e)

Fig. 4 Eye tracking using the UKF algorithm.



(a) (b) (c) (d)

Fig. 5 Eye fatigue detection.

Fig. 6 Snapshots of fatigue detection under realistic background.

4 Performance evaluation

This part of the research is to experimentally and scientifically demonstrate the validity of the proposed system. In order to obtain valuable data, the proposed system was tested adequately in a realistic driving environment. As shown in Table 1, twenty properly qualified drivers between the ages of 25 and 50 served as subjects in this study. Drivers had to have at least one year of experience driving, and they had to be medically qualified and free from controlled substances and alcohol.

Table 1 Twenty drivers served in this study.

Drivers		Total
Male	15	20
Female	5	
With glasses	9	20
Without glasses	11	
Commercial drivers	10	20
Noncommercial drivers	10	

Each participating vehicle is outfitted with an on-board monitoring camera and a data acquisition computer. The proposed method is tested on a Pentium III 1.7G CPU with 128MB RAM in the test vehicles. And the experimental vehicles use ViewQuest VQ680 video cameras to capture driver's images. Driver fatigue detection based on the proposed method can reach 10 frames per second for fatigue tracking. The format of input video is 352×288 pixels. The experimental vehicles are in Table 2.

Table 2 Twenty experimental vehicles in this study.

Vehicle	Quantity	Vehicle configuration
Noncommercial vehicle	2	SUZUKI CH7140
	3	Volkswagen 1.6
	3	Honda CRV SUV
	1	Nissan SUV
	1	Toyota corollar
Commercial vehicle	4	Volkswagen Santana
	3	Volkswagen
	1	Truck
	1	Bus
Total		20

In order to show the validity of the proposed system, this system was tested adequately in a realistic driving environment with 6 subjects of different genders, with/without glasses, day/night driving, commercial/noncommercial drivers, continuous driving time, and under different road conditions. In our study, four different groups of 6 subjects driving in Table 3 were selected to represent four contrasting driving schedules in terms of fatigue-related factors such as time-on-task, motorway versus rural high, and day versus night driving.

Table 3 Four different groups under realistic driving condition.

	Description	Participants	Video
Condition 1: 8-hour daytime motorway driving	Starting at about 9:00 each morning for 3 consecutive days	2 commercial male drivers, without glasses	Video 1
			Video 2
		1 commercial male driver, with glasses	Video 3
		1 noncommercial male driver, without glasses	Video 4
		1 noncommercial female driver, with glasses	Video 5
Condition 2: 8-hour daytime rural highway driving	Starting at about 9:00 each morning for 3 consecutive days	1 commercial male driver, without glasses	Video 6
		2 commercial male drivers, with glasses	Video 7
			Video 8
		1 noncommercial male driver, without glasses	Video 9
		1 noncommercial female driver, with glasses	Video 10
Condition 3: 6-hour nighttime motorway driving	Starting at about 23:00 each night for 3 consecutive days	1 commercial male driver, without glasses	Video 11
		1 commercial male driver, with glasses	Video 12
		1 noncommercial male driver, without glasses	Video 13
		2 noncommercial females drive, without glasses	Video 14
			Video 15
Condition 4: 6-hour nighttime rural highway driving	Starting at about 23:00 each night for 3 consecutive days	1 commercial male driver, without glasses	Video 16
		1 commercial male driver, glasses	Video 17
		1 noncommercial female driver, with glasses	Video 18
		2 noncommercial male drivers, without glasses	Video 19
			Video 20

The experimental results on the test videos are shown as Tables 4∼7.

1) Results of eye tracking

a) Condition 1: 8-hour daytime motorway driving test videos (part sampling videos)

Table 4 Results of eye tracking under Condition 1.

	Video 1	Video 2	Video 3	Video 4	Video 5
Total frames	54730	72640	36460	43210	32450
Tracking failure	247	399	218	172	162
Correct rate	99.55%	99.45%	99.40%	99.60%	99.50%
Average correct rate			99.50%		

b) Condition 2: 8-hour daytime rural highway driving test videos

Table 5 Results of eye tracking under Condition 2.

	Video 6	Video 7	Video 8	Video 9	Video 10
Total frames	43130	32440	40130	53120	37820
Tracking failure	129	65	72	265	144
Correct rate	99.70%	99.80%	99.82%	99.50%	99.62%
Average correct rate			99.69%		

c) Condition 3: 6-hour nighttime motorway driving test videos

Table 6 Results of eye tracking under Condition 3.

	Video 11	Video 12	Video 13	Video 14	Video 15
Total frames	36250	34240	26120	19760	32030
Tracking failure	181	273	151	119	256
Correct rate	99.50%	99.20%	99.42%	99.40%	99.20%
Average correct rate			99.35%		

d) Condition 4: 6-hour nighttime rural highway driving test videos

Table 7 Results of eye tracking under Condition 4.

	Video 16	Video 17	Video 18	Video 19	Video 20
Total frames	30210	18920	16360	23740	24960
Tracking failure	151	91	144	176	175
Correct rate	99.50%	99.52%	99.12%	99.26%	99.30%
Average correct rate			99.34%		

Tables 4∼7 list the results of eye tracking using the UKF algorithm under realistic driving condition. The correct rate of eye tracking is defined as in equation (22), and the comparison of UKF and Kalman filter is shown in Table 8.

$$\text{Correct rate} = \frac{\text{Total frames} - \text{tracking failure}}{\text{Total frames}}. \tag{22}$$

Table 8 Comparison of UKF and Kalman filter.

Algorithm	Correct rate	Average correct rate	Remark
Kalman algorithm under bright pupil and IR illumination	99.10%	99.10%	
UKF algorithm under Condition 1	99.50%	99.47%	Refer to Table 4
UKF algorithm under Condition 2	99.69%		Refer to Table 5
UKF algorithm under Condition 3	99.35%		Refer to Table 6
UKF algorithm under Condition 4	99.34%		Refer to Table 7

From the above table, UKF has only 0.37% tracking improvement than the Kalman filter in [3, 7]. Actually, our method does not use bright pupil and external IR illuminations, so the proposed algorithm has more wide application. The UKF algorithm not only improves the robustness for nonlinear eye tracking, but also can provide more accurate estimation than the traditional Kalman filter.

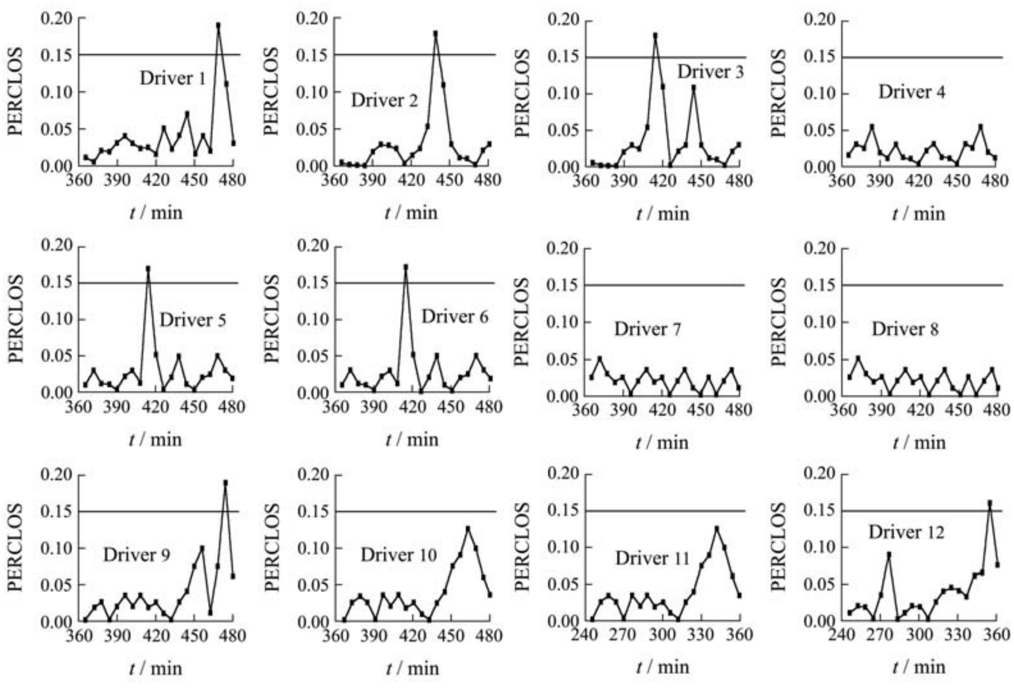
2) Results of fatigue detection

PERCLOS was found to be the best potential measure of fatigue drawn from a range of ocular variables studied above researches. In this paper, the accuracy was scored by using two levels of fatigue thresholds [15] as shown in Table 9. Fig.7 shows the PERCLOS estimates for the 20 drivers.

Table 9 TPERCLOS thresholds.

Questionable	$0.075 \leqslant$ PERCLOS < 0.15
Drowsy (Fatigue)	PERCLOS $\geqslant 0.15$

The study developed a massive database which covers more than 6,000 miles of driving. It includes some 140 hours of video data, 5,040,000 frames of driving record, and 40 hours computing results of PERCLOS. Fig.7 shows the results of fatigue detection on the twenty videos. The last 2 hours data are into 6-min intervals to compute PERCLOS estimates. Because the PERCLOS is only fatigue threshold and detection level after eye tracking, the accuracy of PERCLOS is only scored by the researchers of eye tracking under different tracking algorithms. From Fig.7, fatigue is obvious after long-time driving on the roads. The fatigue probability of nighttime driving is higher than daytime driving. In driver 19 and driver 20, fatigue appears three times (exceeding PERCLOS Drowsy threshold three times). PERCLOS is only fatigue threshold and detection level after eye tracking. Therefore, the accuracy of PERCLOS is only scored by the researches of eye tracking under different tracking algorithms.



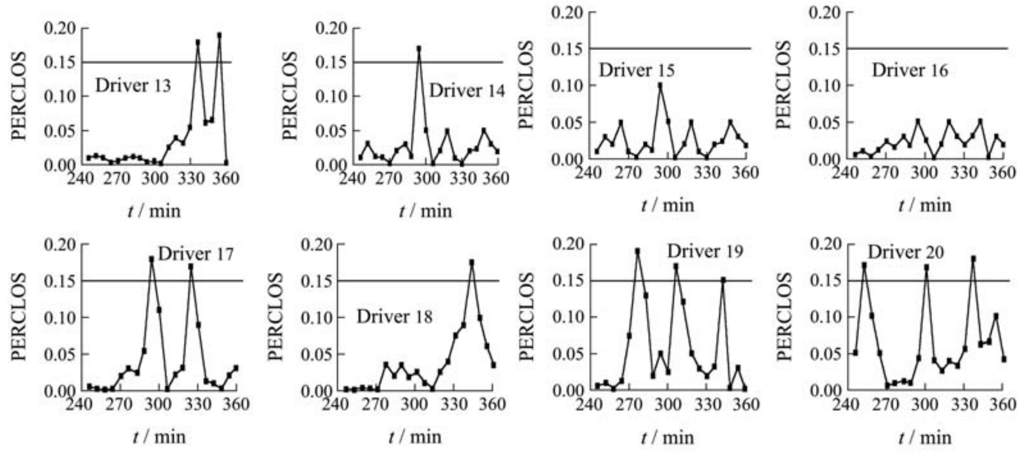


Fig. 7 PERCLOS estimates for 6-min intervals for driver 1∼driver 20.

4.1 Conclusions

In this paper, we proposed a new real-time eye tracking based on a nonlinear unscented Kalman filter for diver fatigue detection. After the face has been located by Haar algorithm, we adopted a set of deterministic sigma points to match the posterior probability density function of eye's movement. At the same time, driver fatigue can be detected using calculated PERCLOS under realistic driving conditions. By experimental results, we have demonstrated that the proposed method improves the robustness and accuracy of eye tracking for driver fatigue.

References

[1] M. Eriksson, P. Papanikolopoulos. Eye-tracking for detection of driver fatigue[C]//*IEEE Conference on Intelligent Transportation Systems*. New York: IEEE, 1997: 314 – 319.

[2] T. Horberry, L. Hartley, G. P. Krueger, et al. Fatigue detection technologies for drivers: A review of existing operator-centred systems[C]//*International Conference on Human Interfaces in Control Rooms, Cockpits and Command Centres*. Edison: Institute of Electrical Engineers, INSPEC Inc., 2001: 321 – 326.

[3] H. Gu, Q. Ji, Z. Zhu. Active facial tracking for fatigue detection[C]//*Proceedings of the Sixth IEEE Workshop on Applications of Computer Vision*. Piscataway: IEEE, 2002: 137 – 142.

[4] W. Horng, C. Chen, Y. Chang, et al. Driver fatigue detection based on eye tracking and dynamic template matching[C]//*Proceeding of the 2004 IEEE International Conference on Networking, Sensing & Control*. New York: IEEE, 2004: 7 – 12.

[5] K. Peng, L. Chen. A roust algorithm for eye detection on gray intensity face without spectacles[J]. *Journal of Computer Science & Technology*, 2005, 5(3): 127 – 132.

[6] W. Dong, X. Wu. Driver fatigue detection based on the distance of eyelid[C]//*Proceeding of IEEE International Workshop on VLSI Design and Video Technology*. New York: IEEE, 2005: 365 – 368.

[7] Q. Ji, Z. Zhu, P. Lan. Real time nonintrusive monitoring and prediction of driver fatigue[J]. *IEEE Transactions on Vehicular Technology*, 2004, 53(4): 1052 – 1068.

[8] S. Singh, N. P. Papanikolopoulos. Monitoring driver fatigue using facial analysis techniques[C]//*Proceedings of International Conference on Intelligent Transportation Systems*. Piscataway: IEEE, 1999: 314 – 318.

[9] D. Comaniciu, V. Ramesh. Mean shift and optimal prediction for efficient object tracking[C]//*Proceedings of the International Conference of Image Processing*. New York: IEEE, 2000: 70 – 73.

[10] P. Papageorgiou, M. Oren, T. Poggio. A general framework for object detection[C]//*Proceeding of the International Conference on Computer Vision*. Piscataway: IEEE, 1998: 555 – 562.

[11] V. Paul, M. J. Jones. Rapid object detection using a boosted cascade of simple features[C]//*Proceedings of the International Conference on Computer Vision and Pattern Recognition*. Piscataway: IEEE, 2001: 511 – 518.

[12] S. J. Julier, J. K. Uhlmann, H. F. Durran. New approach for filtering nonlinear systems[C]//*Proceedings of the American Control Conference*. Piscataway: IEEE, 1995: 1628 – 1632.

[13] S. J. Julier, J. K. Uhlmann. A new method for the nonlinear transformation of means and covariances in filters and estimators[J]. *IEEE Transactions on Automatic Control*, 2002, 47(8): 477 – 482.

[14] S. J. Julier, J. K. Uhlmann. Unscented filtering and nonlinear estimation[J]. *Proceedings of the IEEE*, 2004, 92(3): 401 – 422.

[15] D. F. Dinges, R. Grace. PERCLOS: A valid psychophysiological measure of alertness as assessed by psychomotor vigilance[R]. Washington: Federal Highway Administration, Office of Motor Carriers, 1998.

[16] L. Hartley, T. Horberry, N. Mabbott, et al. Review of fatigue detection and prediction technologies[M]//*National Road Transport Commission Report*. Melbourne: Murdoch University, 2000.

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