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Driver Fatigue Detection System Based on Colored and Infrared Eye Features Fusion

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Abstract: Real-time detection of driver fatigue status is of great significance for road traffic safety. In this paper, a proposed novel driver fatigue detection method is able to detect the driver's fatigue status around the clock. The driver's face images were captured by a camera with a colored lens and an infrared lens mounted above the dashboard. The landmarks of the driver's face were labeled and the eye-area was segmented. By calculating the aspect ratios of the eyes, the duration of eye closure, frequency of blinks and PERCLOS of both colored and infrared, fatigue can be detected. Based on the change of light intensity detected by a photosensitive device, the weight matrix of the colored features and the infrared features was adjusted adaptively to reduce the impact of lighting on fatigue detection. Video samples of the driver's face were recorded in the test vehicle. After training the classification model, the results showed that our method has high accuracy on driver fatigue detection in both daytime and nighttime.

Keywords: Driver fatigue detection, feature fusion, colored and infrared eye features.

1 Introduction

In recent years, fatigue driving has become one of the major causes of traffic accidents except overloading and speeding. It was reported that about half of the traffic accidents that killed more than 10 people at a time occurred when the driver was fatigued [Wang (2010)]. In America, the study by National Highway Traffic Safety Administration (NHTSA) showed that nearly a quarter of crashes involved fatigue driving [Klauer, Dingus, Neale et al. (2006)]. As a result, the research on fatigue monitoring technology is of great significance to the road traffic safety.

When the driver is fatigued, the perception of traffic flow, the ability to control the vehicle and the prediction of the dangerous situation all have a significant downward trend, which will lead to a sharp increase in the probability of traffic accidents. Fatigue driving is 4-6

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times more likely to cause traffic accidents than normal driving [Klauer, Dingus, Neale et al. (2006)]. As a result, more and more attention has been paid on driver-fatigue detection in the world. The European Union stipulated that new cars will be forced to install 12 safety facilities including fatigue monitoring from 2021.

Fatigue is a kind of mental state which cannot be measured directly, so we can only evaluate the level of fatigue indirectly by analyzing the driver's physiological parameters and external behaviors, and the operating characteristics of the vehicle. However, there are many difficulties in fatigue detection. The inconvenience of professional monitoring equipment and individual differences makes it very difficult to obtain the physiological parameters of the driver in real time. To obtain steering wheel angle via CAN bus, the vehicle is required to support electronic power steering and electronic stabilize program. Otherwise, special sensors must be installed, which means that the calibration work needs to be carried out. As a result, it is a general and convenient method to evaluate the fatigue state by analyzing the expression of the driver, which is worthy of further study. Eyes, as one of the most salient facial features reflecting individuals' fatigue states [Song, Tan, Chen et al. (2013)], have become one of the most remarkable information sources in face analysis. In this paper, the status of the eyes was selected as the basis of fatigue detection. The main ideas are:

(1) Both colored lens and infrared lens were used for image capture.

(2) Dlib was applied for eye-area recognition, and features of colored and infrared images were used for fatigue detection.

(3) By adjusting the weight values according to the different light intensity in the SVM model, the robustness of detection in dark environment was improved.

2. Related works

Over the past decades, with the development of computing science and image processing technology, more and more researchers have been exploring image-based fatigue detection method due to its flexibility and non-contact. The most important issues are the detection of the eye features and the discrimination of the fatigue state.

2.1 Detection of the eye features

The detection of eye position and characteristics is the basis of fatigue detection.

Zhou et al. [Zhou and Geng (2004)] projected the pixel values of each point in the eye image to the X and Y directions to get the integral projection curve, and projected the change of the pixel values to the X and Y directions to obtain the difference integral projection curve. The positioning accuracy of the eyes was improved by weighting the two curves together.

In some research [Li, Niu, Yang et al. (2015); Mandal, Li, Wang et al. (2016); Wu, Lee, Wu et al. (2010)], Adaboost algorithm was used to locate the eyes, and Harris corner detection was applied to get the sight of eyes.

Dong et al. [Dong, Zhang, Yue et al. (2016)] analyzed the Histogram of Oriented Gradient of the eye-area, and used Random Forest classifier to distinguish the fatigue state. Based on spectral regression and adaptive integration of multi-model detections, Mandal et al.

[Mandal, Li, Wang et al. (2016)] proposed an approach to estimate the continuous level of eye openness and a fusion algorithm to estimate the eye state.

Zhang et al. [Zhang, Cheng and Zhang (2012)] used active shape model (ASM) in the face image to improve the adaptability to complex light, and used stacked shape model to locate eye feature points. On this basis, an improved deformable template was applied to locate the contour points of the eyes, and the opening-closing degree of the eyes was obtained by calculating the distance between the upper and lower eyelids.

By training the feature points of the upper, lower eyelid and pupil, Moriyama et al. [Moriyama and Kanade (2007)] got the Active Appearance Model (AAM) of these parts, and achieved the information of the shape and location of the eyes and pupil.

2.2 Fatigue discrimination based on the eye state

In 1994, Wierwille et al. [Wierwille and Ellsworth (1994)] proved that the eye closure time could reflect the driver's fatigue state to a certain extent. Carnegie Mellon Institute put forward PERCLOS (Percentage of Eyelid Closure overt the Pupil over Time) as the physical quantity to measure fatigue after some research and demonstration. Since then, a large number of researchers regarded this as an important parameter to judge the fatigue state of drivers, and have done a lot of work on this method [Mandal, Li, Wang et al. (2016); Kuang, Mao, Huang et al. (2016); Peng, Dong and Chen (2014); Anirban, Anjith, Happy et al. (2013); Zhang and Li (2008)].

Wu et al. [Wu and Chen (2008)] captured the driver's face image through a CCD camera mounted on the instrument panel, and used the fuzzy logic algorithm to extract the driver's eyes-closed time and blink frequency to determine the driver's fatigue level.

Kuang et al. [Kuang, Mao, Huang et al. (2016)] used a Gauss sclera model based on YCbCr color space to detect the face region. They considered the sclera area as the eye-opening index so as to judge the state of fatigue. It was proved that this method achieved an ideal precision under good lighting condition.

Zhang [Zhang (2011)] selected 11 parameters related to the driver's eyes and established the fatigue feature space based on the action features of the eyes. Then they set up the fatigue state based on the prior knowledge obtained from the training samples in the early driving stage. On this basis, the fatigue state of the driver is further inferred through the Bayesian confidence network pair.

Jo et al. [Jo, Lee, Park et al. (2014)] used edge projection histogram to recognize the open and closed state of eyes, and extracted PERCLOS and blink frequency as the features according to the recognition results. SVM was applied as the classifier to distinguish the fatigue state of drivers.

3 System architecture

In this work, we proposed a real-time system for monitoring the driver's fatigue status any time of day. The architecture is shown in Fig. 1.

In order to achieve a higher accuracy of fatigue detection, a binocular camera which contains a colored lens and an infrared lens was used. The real-time videos of the two channels were processed separately. Moreover, a photosensitive sensor was used to adjust the weight values to adapt to different light environment. The main steps are:

(1) Dual videos acquisition;

(2) Face detection and labeling of face landmarks;

(3) Calculate the aspect ratio and blink of the eyes as the features for fatigue detection;

(4) According to the illumination, the appropriate weight values are selected for the feature sets from colored lens and infrared lens separately. The fatigue level of the driver is estimated.

The system will be described in detail below.

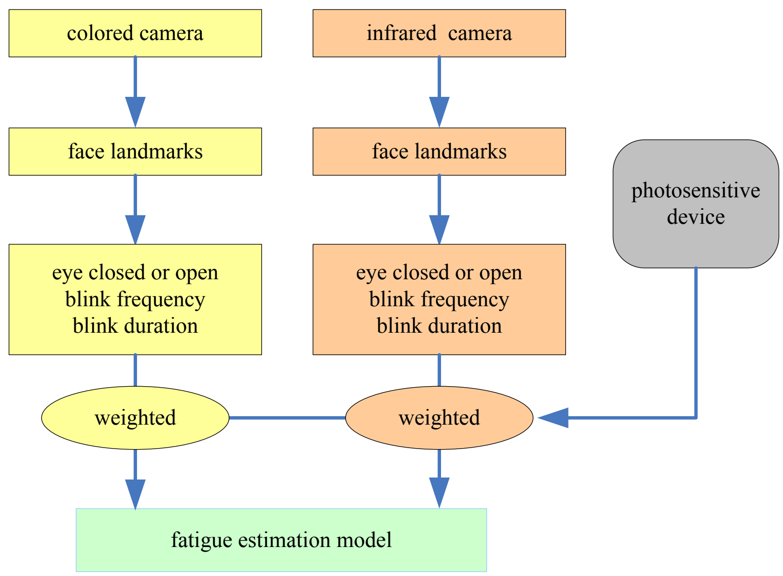

Figure 1: System architecture

3.1 Dual-lens camera

Traditional RGB cameras can obtain fairly good images under ideal lighting conditions. However, the light in the cab is usually too dim, which will result in the increase of noise and the decrease of definition. So, we used a dual-lens camera, including a colored lens and an infrared lens with three IR LEDs as well. The images of the two channels were collected and processed separately by the system until the relevant parameters of the eyes state are obtained. Then, according to the illumination in the scene, the weight values of each feature from the two channels were adjusted by the decision system to determine the driver's fatigue level.

The camera is as shown in Fig. 2, and the parameters of the camera are given in Tab. 1.

Figure 2: Dual-lens camera

Table 1: Parameters of the camera

Parameter	Specifics
Pixels	2.0 mega pixels RGB lens+2.0 mega pixels infrared lens
Infrared region	Narrow band 850nm
Field of view	90°
Distortion	<1.0%
Sensor type	CMOS
Video format	MJPG/YUV2

3.2 Eye area landmarks

In order to get the area of the eyes, we need a technique for extracting facial feature points. After some experiments and comparison, the facial landmark detection function in Dlib-Library seemed to be able to achieve an ideal processing speed while ensuring the accuracy of detection in our application.

The Dlib-Library was constructed on the basis of a general framework proposed by Kazemi et al. [Kazemi and Sullivan (2014)] which learns an ensemble of regression trees that can optimize the sum of square error loss. The algorithm adopts a cascade of regression factors [Dollár, Welinder and Perona (2010); Cao, Wei and Wen (2014)], and generates a model by using a serial of calibrated face images as a training set. The basic principle of the algorithm is as follows.

Symbol definition:

- I: an image
- x_i: the x, y -coordinates of the i-th facial landmark in image I
- $S = (x_1^T, x_2^T, \dots, x_p^T)^T \in \mathbb{R}^{2p}$: the coordinates of all p facial landmarks in image I
- $\hat{S}^{(t)}$: the current estimate of S
- $r_t(.,.)$: the regressor

Each regressor predicts a new vector based on the image and $\hat{S}^{(t)}$. Then the improved estimate is obtained.

$$\hat{S}^{(t+1)} = \hat{S}^{(t)} + r_t(I, \hat{S}^{(t)}) \tag{1}$$

Geometric invariance was introduced into the process of detection. With the progress of the cascade, the precise location of landmarks on the face could be obtained. In this paper, the model of 70 face-landmarks was used, as shown in Fig. 3.

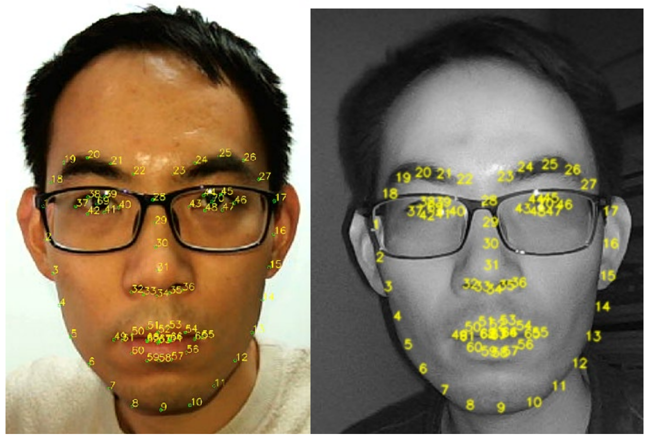

Figure 3: Location of facial landmarks (left: colored, right: infrared)

3.3 Eye status and blinks

For the input of fatigue classification model, the following eye features from both colored and infrared channels were selected [Pan, Li and Xu (2011)].

● Duration of Eye Closure (DEC)
● Frequency of Blinks (FB)
● Percentage of Eyelid Closure over the Pupil over Time (PCT)

At the same time, the light conditions in the cab should be taken into account by a photosensitive device:

● Light intensity (LI)

According to the recent studies, it was suggested that duration of eye closure has the highest performance to detect fatigue compared to other ocular indicators [Puspasari, Iridiastadi, Sutalaksana et al. (2019); Schleicher, Galley, Briest et al. (2008)]. When the eyes blink, the DEC of each blink was calculated, and then was input to the model along with the other parameters.

Another eye feature of fatigue is frequent blinking, and the other two features FB and PCT were based on the eye dynamics and blink patterns [Sree, Srinivasan, Nagarajan et al. (2019); Divjak and Bischof (2009)]. In order to improve the resolution of detection, the two parameters were updated every 20 seconds rather than 1 minute as applied in the previous works [Wierwille, Ellsworth, Wreggit et al. (1994); Dinges and Grace (1998)].

By detecting the aspect ratio of the eyes, we were able to tell whether the eyes were open or closed by setting a threshold of the ratio, As shown in Figs. 4 and 5, on the basis of the detection, the eye features could be calculated [Nabil, Steve and Khaled (2018)].

Figure 4: Aspect ratio of an eye (left: open, right: closed)

The calculating formula of aspect ratio was designed as:

$$\frac{\|P_{38}-P_{42}\|+\|P_{39}-P_{41}\|}{2*\|P_{37}-P_{40}\|} \tag{2}$$

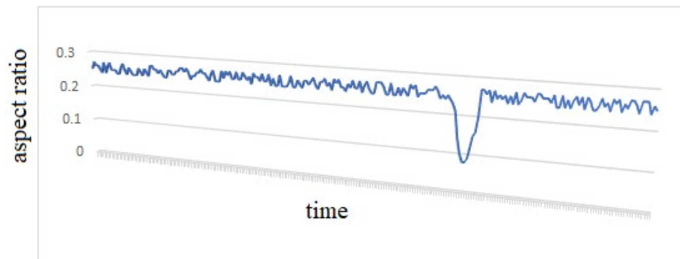

Figure 5: Aspect ratio curve of a blink

3.4 Fatigue detection model

Aiming at the poor robustness of fatigue detection based on single feature, we adopted a support vector machine (SVM) model based on pre-extracted multi feature fusion [Li, Shen, Dai et al. (2019)] which is faster than convolutional neural networks. As Chapter 3.3 mentioned, the feature set is designed as:

$\{DEC^c, FB^c, PCT^c, DEC^i, FB^i, PCT^i, LI\}$

where X^c indicates the feature from colored lens and X^i indicates the feature from infrared lens.

SVM is a new machine learning method developed on the basis of statistical learning theory in the mid-1990's, which minimizes the structural risk and seeks the balance between the learning ability and the complexity of the model according to the limited sample information to obtain the best generalization ability.

Given the linear separable sample(x_i, y_i), $i = 1,2,\ldots,n$,$x \in R^d$, and $y \in \{+1,-1\}$indicates the classification. The general form of the linear discrimination function is $g(x) = wx + b$. The discriminant function is normalized so that all samples reach the condition: $|g(x)| = 1$ and the margin of classification is $\|w\|/2$ [Byun and Lee (2002)]. As a result, the optimal condition of classification is:

$$min(\|w\|^2/2) \text{ s. t. } y_i[wx + b] - 1 \geq 0, i = 1,2,\ldots n \tag{3}$$

where w is the weight vector in Hilbert space and $b$is the classification threshold.

After Lagrange transformation, the optimal classification function is:

$$f(x) = sgn\{w^* x + b^*\} \tag{4}$$

$$f(x) = sgn\{\sum_{i=1}^{n} a_i^* y_i (x_i x) + b^*\} \tag{5}$$

where $a_i \geq 0$, w^* is the weight vector of optimal classification plane, and b^* is the optimal classification threshold.

For linear inseparable issues, relaxation parameter $\varepsilon_i \geq 0$ should be introduced:

$$min(\|w\|^2/2 + C\sum_{i=1}^{n} \varepsilon_i) \text{ s.t. } y_i[w_i x_i + b] - 1 + \varepsilon_i \geq 0, i = 1,2,\dots n \tag{6}$$

where C is a constant greater than zero, called the penalty term.

4 Experiments

Before training the model, we recorded the sample videos in the test vehicle as shown in Fig. 6. Both colored and infrared channels were recorded simultaneously as Fig. 7.

Due to the danger of collecting facial data in real driving scenes, the drivers involved in this test were all Chinese with ample driving experience. Four male and four female drivers participated in the experiment as volunteers, five of whom wore glasses. In order to get the data set with fatigue symptoms, we asked the test drivers to stay up for more than 15 hours and drive the vehicle to and from in an area with less traffic. Meanwhile, the facial expressions of the drivers were recorded in videos. Then the video clips with fatigue performance were edited and merged through manual filtering.

In order to improve robustness of the model, the samples were captured at different times of day. All the samples were put into the model for offline training. The training set and test set are designed as Tab. 2.

Figure 6: Camera in test vehicle

Figure 7: Field of vision (left: colored, right: infrared)

Table 2: Dataset designing

Length of video	Training set		Testing set	
	Daytime	Nighttime	Daytime	Nighttime
Normal	49 h 18 m 6 s	43 h 26 m 41 s	3 h 13 m 57 s	2 h 57 m 29 s
Fatigue	4 h 47 m 39 s	3 h 54 m 27 s		

After the test set was processed by the model, the result was compared with the outcome annotated manually, as shown in Tab. 3.

It should be noted that, in this work, we focused on the identification of the drivers' fatigue state and the precision and recall of fatigue category were calculated.

Table 3: Result of the experiments

	Testing set	
	Daytime	Nighttime
Fatigue times via manual screening	137	121
Correctly detected by the model	133	116
Missed by the model	4	5
Wrongly detected by the model	2	4
Precision	98.52%	96.67%
Recall	97.08%	95.87%

According to the results, the proposed method showed a high performance not only in the bright daytime, but also when it is dark at night.

Four recent studies applicable for both daytime and nighttime were chosen as a comparison with our method as Tab. 4. It is proved that the precision of driver fatigue detection can be effectively improved.

Table 4: Comparison of methods and results

Author	Method	Precision
Zhang et al. [Zhang, Liu, Tang (2015)]	Head pose and eye state	93.33%
Deng et al. [Deng and Wu (2019)]	Features of the eyes and mouth	91.83%
Mandal et al. [Mandal, Li, Wang et al. (2016)]	Head-shoulder detection and eye openness	95.18%
Li et al. [Li, Wang, Du et al. (2019)]	Features of both the eye and mouth regions	90.71%
Ours	Colored and infrared eye features fusion	97.59%

5 Conclusion

In this paper, a novel driver fatigue detection method is proposed. The influence of light change on fatigue detection can be greatly reduced by combining multi-mode features of color image and infrared image with variable weight. In the next phase of the research, more facial features could be introduced into the detection model, and other measures such as confusion matrix, recall and F1 score could be added to improve the detection performance.

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