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Multi-feature analysis fatigue driving based on Conditional Local Neural Fields algorithm detection method

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Abstract. In order to effectively strengthen the monitoring technology of fatigue driving and reduce the incidence of traffic accidents, this paper proposes a new method based on conditional local neural fields algorithm for comprehensive evaluation of fatigue driving state. At present, most of the fatigue driving detection algorithms are based on extracting a single characteristic index, which is strict in environmental requirements and not high in detection. In this paper, the HOG feature is combined with the CLNF algorithm to implement face detection and feature point localization. Then, the EPnP algorithm is used to estimate the head anomaly frequency based on the feature point information, and the blink frequency is calculated according to the EAR eye length aspect ratio concept according to the feature points around the eye. Finally, the threshold set by the P80 fatigue detection standard in the PERCLOS method is integrated, and the distributed information fusion strategy is used for fatigue evaluation. Experimental results confirm the effectiveness of the method.

1. Introduction

At present, fatigue driving has become a major hidden danger of traffic accidents. Therefore, in order to reduce the incidence of traffic accidents, it is particularly important to study the automatic detection technology of fatigue driving.

At present, the detection technology of fatigue driving can be divided into three methods based on vehicle behavior detection, driver physiological characteristic detection and driver behavior detection. Hongtao Li et al. [1-2] studied the characteristics of cars, including steering wheel parameters and vehicle trajectory. But this method is greatly influenced by the outside world, for example: the type of motor vehicles, road familiarity and driving environment. Xulei Yu et al. [3-4] studied the driver’s brain signal characteristic data, considering that the portable instruments may affect the driving sense, this method should not be promoted. Based on the driver behavior detection method, the face feature can be the main detection object. Weifeng Liu et al. [5-6] studied the detection method based on feature analysis of the facial features, which have low detection accuracy.

In this paper, a new method bases on conditional local neural fields algorithm for fatigue detection of facial multi-feature analysis is proposed. The main purpose is to use the face gradient histogram (HOG) based on face detection algorithm and one of the most mature face recognition CLNF algorithm to achieve driver facial feature extraction. Then use the extracted feature points, the EPnP algorithm and the EAR eye length aspect ratio method can be used to calculate the head attitude abnormal rate and the blink frequency respectively. Combined with the P80 fatigue standard in PERCLOS algorithm, the distributed information fusion strategy can be used for fatigue evaluation. This ensures good robustness and the detection accuracy can reach 94%.
2. Related work

The fatigue detection method flow is shown in Figure 1:

![Figure 1. Technical route](image)

The following is a three-part introduction to the research method, including two algorithms and multi-feature calculation analysis method. In this section, there will be an introduction to the algorithm basis used for face detection and face localization.

2.1 HOG

The HOG feature detection algorithm was proposed by the French research institute Dalal et al. [7] on CVPR-2005, which is a shape-edge feature-based description operator. Compared with other detection algorithms, since HOG operates on the local grid unit of the image, it can maintain good invariance to the geometric and optical deformation of the image, so it is more suitable to be used in a fatigue driving detection environment.

2.2 CLNF

On the basis of 2.1, the face feature point location is performed by the Conditional Local Neural Fields algorithm. The algorithm is mainly proposed by Tadas Birutaiči [8], owning the advantages of high precision and good robustness. Compared with AAM and CLM models, it is more suitable for occasions where the head posture changes frequently, such as driving environment.

The CLNF algorithm is an innovation in the CLM algorithm, both use the same framework. The algorithm flow can be divided into two phases: the model construction phase and the feature point detection phase. The model construction is divided into two steps: shape model construction and patch model construction.

The feature point detection process is shown in Figure 2. The first step is to construct a shape model, which mainly includes feature point coordinate information, and the second step represents a patch model, which includes image information of various areas of the facial features. In the CLNF algorithm, based on the same shape model construction as the CLN algorithm, the patch model has been changed, and a new patch model combined with LNF [9] is adopted, which can better capture the relationship between feature points and pixels.

![Figure 2. Feature point detection process](image)

The results of the algorithm detection are shown in Figure 3. Multi-pose and closed-eye states can detect facial feature points:
3. Calculation Method

After the face detection and feature point positioning of the target, it is necessary to calculate and analyse the facial feature points, including eye and head state information combined with the PERCLOS algorithm, and evaluate the fatigue degree based on the fatigue feature comprehensive results.

3.1 PERCLOS algorithm

PERCLOS [10] is a very effective fatigue driving judgment method proposed by the US Federal Highway Administration and the National Highway Traffic Safety Administration through the comparison of nine fatigue testing indicators. The P80 in the PERCLOS method is suitable to detect the driver’s fatigue detection standard: when the eyelid obstructs the area of pupil to more than 80%, the eye is closed, and then the eye closing time is calculated as a percentage of the unit time.

At the same time, the closed state of the eye is related to the open area of the eye, so the change in this area reflects the degree of opening of the eye. The eye test is shown in Figure 5(a) and the eye model is shown in Figure 5(b):

Can draw the equation (1):

$$F = \frac{S}{S_{\text{max}}} = \frac{\pi ab}{\pi a_{\text{max}} b_{\text{max}}} = \frac{\pi (y_{40} - y_{38})(x_{39} - x_{36})}{\pi (y_{40} - y_{38})_{\text{max}} (x_{39} - x_{36})_{\text{max}}}$$  \( (1) \)

\( S_{\text{max}}, a_{\text{max}}, b_{\text{max}} \) is the value when the eye is opened at the maximum. \( F \) represents the degree of blinking of each frame of the picture, so the calculated \( f_p \) blink frequency is an indicator for assessing fatigue driving.

3.2 Head posture abnormal frequency calculation

This section uses the EPnP algorithm[11]. The rotation angles of roll, yaw and pitch are solved by algorithm. The pitch represents the tilt angle of the front and rear direction, and the tilt angle is related to the driver’s nod state. Assume that the nodding frequency is given by equation (2):

$$f_n = \frac{N_{TN}}{N_T}$$  \( (2) \)

Among them, \( N_{TN} \) is the number of nodding actions at time \( T \), and \( N_T \) is the total number of frames of video in time \( T \). \( f_n \) is an evaluation index for evaluating fatigue driving.
Ferrariod et al. [12] found that adult head posture rotation angle has a fixed range, referring to the P80 standard of the PERCLOS algorithm, the 20% angle change is used as the criterion for fatigue judgment. Therefore, when the average change of the Roll rotation angle is greater than 8.18° or the average change of the Yaw rotation angle is greater than 15.8°, it is judged that the driver's head is in an abnormal state. Assume that the abnormal state frequency $f_h$ is the equation (3):

$$f_h = \frac{N_{TH}}{N_T}$$

(3)

$N_{TH}$ is the number of frames in which the abnormal state is detected in time T, and $N_T$ is the total number of frames in the time T. $f_h$ is an evaluation index for evaluating fatigue driving.

3.3 Blinking frequency calculation

When the driver is in a fatigue state, the blink frequency is increased, and it is possible to judge whether the driver is fatigued by detecting the number of blinks of the driver per unit time. This paper is based on the concept of Soukupová and Čech based on the long aspect ratio [13] of the feature points around the eyes. Use this concept to determine if the eye is closed and calculate the frequency of blinking. The principle of eye length aspect ratio is shown in Figure 5.

![Figure 5](image)

The six feature points P1 to P6 are six feature points of the corresponding eye in the face feature point. The aspect ratio will be significantly different when the eyes are opened and closed. When the eyes are closed, the aspect ratio will have a significant downward slope. The formula for calculating the aspect ratio is given by equation (4):

$$r_{EAR} = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2\|P_4 - P_3\|}$$

(4)

When the $r_{EAR}$ is 0.15, it is the aspect ratio dividing line. When it is less than 0, 15, it is recorded as a state of closed eyes. Assume that the blink frequency $f_b$ is the equation (5):

$$f_b = \frac{N_{TB}}{N_T}$$

(5)

$N_{TB}$ is the number of blinking actions occurring in the time period T, and $N_T$ is the total number of frames of the video in the time T. $f_b$ is an evaluation index for evaluating fatigue driving.

3.4 Multi-feature comprehensive information analysis

In this paper, multi-feature comprehensive analysis is used to judge fatigue driving, so it is necessary to perform statistics and analysis on multiple test data. A distributed information fusion strategy will be adopted. Through some experiments, Table 1 shows the average threshold determination of each feature.

| Fatigue characteristics | Awake- Fatigue | Fatigue-Severe fatigue |
|-------------------------|---------------|------------------------|

Table 1. Fatigue threshold of each indicator
According to the threshold information of Table 2, each attribute data is discretely processed. Divided into three levels, specifically 0: awake; 1: fatigue; 2: severe fatigue. Finally, based on the decision tree to determine the final degree of fatigue.

4. Analysis

4.1 Performance Analysis of CLNF Algorithm
The CLNF algorithm can be used to verify the face positioning by experiments. The positioning effect is shown in Figure 3. In order to highlight the superiority of CLNF with respect to other facial feature localization algorithms, experiments are conducted on the face dataset Multi-PIE. The Multi-PIE face database includes 337 faces of different poses, expressions, and illuminations. 750K+ face image. The positioning comparison results are shown in Table 2.

Table 2. Positioning comparison result

| Positioning method | Average time per image /s | Accuracy /% |
|--------------------|---------------------------|-------------|
| AAM                | 1.0                       | 93.45       |
| CLM                | 0.6                       | 98.12       |
| CLNF               | 0.4                       | 99.23       |

It can be seen from Table 1 that the CLNF face feature point localization algorithm has obvious advantages in terms of average time, success rate and error rate. Among them, AAM is called Active Appearance Model, which uses the global texture method to statistically model the texture, and has lower performance than the CLM algorithm.

4.2 Experimental result
According to the detection algorithm and multi-feature comprehensive analysis above, the results are shown in Table 3.

Table 3. Fatigue driving assessment results

|                    | Number of samples | the correct number | The error number | Recognition rate |
|--------------------|-------------------|--------------------|------------------|------------------|
| Awake              | 300               | 282                | 18               | 94%              |
| Fatigue            | 200               | 189                | 11               | 94.5%            |
| Severe fatigue     | 100               | 100                | 0                | 100%             |

In order to illustrate the advantages of the proposed method to the traditional detection algorithm, the recognition rate of this method are compared with others. The results are shown in Table 4. Using the ASM model to detect fatigue accuracy, which is similar: the accuracy is less than 92%. Therefore, the method proposed in this paper has certain advantages compared with the traditional detection method [14-16].

Table 4. Fatigue method detection comparison

| Detection method               | lab environment | Recognition rate |
|--------------------------------|-----------------|------------------|
| Adaboost and ASM              | indoor          | 90%              |
| ASM and Skin color detection  | Indoor          | 91.4%            |
| Adaboost and Pupil positioning| indoor          | 92.8%            |
| Method of this paper           | indoor          | 94%              |

5. Conclusion
In this paper, the HOG feature is combined with the CLNF algorithm to realize face detection and feature point localization while the multi-feature index is combined to evaluate the fatigue degree. Compared with the traditional AAM and CLM algorithms, the CLNF algorithm can be more robust and suitable for complex environments. At the same time, multi-feature information fusion can be more comprehensive and reliable than traditional single-indicator detection methods, with a higher accuracy.

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