

# 2200469

*by* Haozhe Zhang

---

**Submission date:** 22-Apr-2023 11:53AM (UTC+0100)

**Submission ID:** 202956706

**File name:** 39071\_Haozhe\_Zhang\_2200469\_493226\_1137281452.docx (215.14K)

**Word count:** 6091

**Character count:** 35800

---

# **Fatigue Driving Detection Method Based on Multi-source Information Fusion**

## **1. Introduction**

Drowsy driving has become a severe social problem in the past few decades. The report of the World Health Organization mentions that fatigue driving is very likely to lead to road traffic accidents, which seriously affects driving safety. Fatigue and drowsiness can lead to impaired attention, judgment, and slower reaction time.

Fatigue driving poses severe risks to road safety and driver safety. The rapid development of motorization has dramatically increased the occurrence of traffic accidents, leading to an increase in the number of casualties. Drunken driving is also a factor that increases road hazards, and the public still does not pay attention to this reason. Therefore, conducting in-depth research on the degree of correlation between traffic accidents and fatigue is essential. A road safety research report in the United States estimates that the number of people falling asleep while driving is increasing, leading to countless accidents. If there is an effective method to monitor this situation and remind drivers, many fatal accidents can be avoided.

With the continuous increase in demand for road transportation, heavy truck transportation has become the primary mode of land transportation. The constant development of commercial vehicle networking technology, especially the advancement of cloud computing and communication technology, has improved the economy and convenience of heavy truck transportation. The express delivery industry has high requirements for preventing fatigued driving behavior due to its high timeliness, frequent nighttime driving, and strict cost control. While driving a vehicle, the driver determines the driving plan and needs to judge the surrounding environment and path. Due to each individual's different driving habits and psychological conditions, they will exhibit other behaviors when facing fatigue, which means they will exhibit various driving behaviors. Therefore, accurately and quickly detecting the driver's response to the environment is significant [2]. Driving behavior is a complex action that describes the driver's rapid response to changes in the road based on their state in the scene and surrounding environment. The randomness and uncertainty of driving

behavior are one of the many causes of traffic accidents, and it is still considered a challenging topic today[3].

When heavy truck drivers experience fatigued driving behavior, timely detection and reminders to ensure driving safety are crucial for improving transportation efficiency.

## 2. Literature Review

There are three traditional detection methods for driving behavior detection in the system: based on driver physiological factors, based on facial image information, and based on vehicle motion information. The technical methods of each detection method are different, but they all belong to the detection of physiological changes caused by driver fatigue driving. The characteristics of each detection method are shown in Table 1:

**Table 1 Comparison of Fatigue Driving Detection Methods**

| No | Detection method                    | Features                                                                                                           | Advantages                                                             | Disadvantages                                                                                                                               |
|----|-------------------------------------|--------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| 1  | physiological information detection | Direct contact with the driver through sophisticated medical equipment                                             | Strong objectivity and high accuracy                                   | Intrusive, heavily disturbed by the outside world, disturbing the driver's driving, difficult to obtain and expensive measuring instruments |
| 2  | facial image Information detection  | Quickly locate and recognize facial features, and respond to driver behavior in real time through machine learning | Strong objectivity, high convenience, low cost and easy implementation | Very susceptible to changes in external light and obstructions, reducing the accuracy of detection                                          |
| 3  | vehicle                             | Judging the                                                                                                        | The method of                                                          | Rely on personal driving                                                                                                                    |

|  |                                  |                                                                                                                                           |                                                                          |                                                                                  |
|--|----------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------|----------------------------------------------------------------------------------|
|  | movement<br>feature<br>detection | driver's<br>behavior of<br>manipulating<br>the vehicle,<br>thus indirectly<br>judging<br>whether the<br>driver is in an<br>abnormal state | feature<br>extraction is<br>direct and the<br>detection speed<br>is fast | habits, difficult to judge<br>in different road<br>conditions, low<br>robustness |
|--|----------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------|----------------------------------------------------------------------------------|

Summary: Any detection method has its own advantages and disadvantages. As driving behavior is a complex physiological and psychological phenomenon, the fatigue index of a single channel cannot truly and accurately reflect the driving state, and the information extraction process is vulnerable to complex external factors. Environmental interference (such as strong light, bumpy road, driver's driving habits, etc.), so the fatigue driving detection method based on a single information source is not reliable.

## 2.1 Fatigue Driving Analysis Based on Physiological Characteristics

Detection based on physiological information requires direct contact with the driver through complex medical equipment. This detection method is the most objective and has high accuracy. However, due to its invasiveness and severe external interference, it will inevitably cause significant interference to the driver's driving process. The required measuring instruments are difficult to obtain and expensive, so this method is difficult to promote in practical applications.

Detection based on physiological information requires direct contact with the driver through sophisticated medical equipment. This detection method is the most objective and has high accuracy. However, due to its intrusiveness and severe external interference, it will inevitably cause significant interference in the driving process of the driver. The required measuring instruments are difficult to obtain, and the price is high, so this method is difficult to promote in practical applications.

Physiological indicators can change under different driving conditions, so it is possible to determine whether fatigued driving behavior occurs based on changes in the driver's physiological signals. Babaeian et al. (2019) proposed a machine learning-

---

based technique that analyzes the physiological signal responses of drivers (ECG measurement of HRV signals) to detect whether drivers engage in fatigued driving and drowsy behavior [4]. Two machine learning algorithms, KNN and SVM, extract two different feature sets, WT and SFFT, to detect the driver's driving status. Both detection methods have an accuracy rate higher than 80%. The accuracy of KNN based on STFT features is 85.5% for males and 81.4% for females. After experiments, it was found that KNN has a higher performance in detecting driver drowsiness compared to SVM. Nemcova et al. conducted a series of tests to compare the dataset, environment, and stress regarding driving fatigue and stress using different physiological detection methods [5].

Haghani et al. reviewed driver behavior detection methods based on neuroimaging. Detection methods based on physiological information such as fNIR (near infrared) spectroscopy and MEG (magnetic brain imaging) can be used to detect driver fatigue, distraction, poisoning, and decision-making tasks, of which EEG and fMRI (functional magnetic resonance imaging) are the most commonly used methods [6]. Tian et al. conducted a literature review on fatigue monitoring using EOG signals through the protocol mentioned in the paper, focusing on the performance of physiological signals in abnormal behavior detection [7]. Gu et al. used continuous wave Doppler radar for fatigue detection [8]. Place continuous wave radar in the vehicle to obtain the driver's breathing and heart rate during driving to study and judge abnormal driving situations. Purnamasari PD et al. used wearable electrocardiogram detection devices to detect driver drowsiness and studied the physiological signal changes of drivers [9]. It comprises a Zephyr BioHarness detection device and an application program for collecting and transmitting electrocardiogram signals. After establishing the connection, the physiological signal response of the tester is detected to determine the state (awake/tired), and the ECG signal is transmitted to the Android application to see the driver's condition and record it. In this scheme, there are two algorithms implemented. Firstly, the first algorithm is based on the adaptive setting of heart rate thresholds from the driver's awake dataset, derived from cognitive neurodynamic. The second method of setting the point for the algorithm is not to use heart rate but to detect driver status and alarm by finding the ratio of low frequency to high frequency in the ECG signal.

Detection based on physiological information requires direct contact with the driver through complex medical equipment. This detection method is the most objective and has high accuracy. However, it's invasiveness and severe external interference will

---

inevitably cause significant interference to the driver's driving process. The required measuring instruments are difficult to obtain and expensive, so this method is difficult to promote in practical applications.

## **2.2 Fatigue driving analysis based on facial information**

There is an undeniable relationship between the facial expressions and behavioral movements reflected by drivers and the occurrence of fatigue driving. When a person is in an abnormal state, the state of their eyes will also undergo corresponding changes. The pupil diameter and Ha opening frequency vary with the degree of fatigue, making them the most widely used indicators for detecting abnormal driving behavior. Caryn and Rahadanti applied various driver behavior drowsiness detection methods for comparative analysis [10], such as driver's eye-opening and closing degree, frequency and frequency of Zhang Ha, support vector machine judgment, and many other detection model methods. At the same time, the characteristics and shortcomings of various detection methods were analyzed, and improvement methods and enhancement measures were proposed. The application in this field elaborates on driver fatigue characteristics' characteristics and key detection schemes. Li et al. established a micro face detection model by improving the YOLO3 neural network [11], eliminating the influence of human uncertainty in the facial feature extraction process, and designed an eye-mouth SVM classifier based on blink frequency and yawn features. Classification of driver fatigue. Based on the extracted 18 fatigue features [12]. Friedrich et al. used the SFPS algorithm for screening and designed a neural network fatigue detection model. Ji Yingyu et al. designed an algorithm integrating multiple factors and driver status to detect fatigue behavior [13]. This study used convolutional neural networks for face detection and feature point detection.

Fatigue detection models were established by combining the two features of Zhang Ha times and the degree of eye-opening and closing. Ye et al. proposed a method for fusing facial key point positions to locate driver facial expressions and human body positions to immediately identify these abnormal driving behaviors and warn drivers [14]. Firstly, the OpenPose neural network model is used to represent key points of the body, face, and hands. These data are used to determine dangerous driving behavior, select the Dlib model to detect facial key points and transmit them to detect the degree of eye-opening and closing to display fatigue, and extract driver motion features to supplement human posture data. Mumcuoglu et al. developed a driving behavior

---

recognition algorithm using long-term memory (LSTM) network using the driver model of IPG's TruckMaker. They designed six driver models based on longitudinal and lateral acceleration [15]. Xing and Zhang designed a driver behavior recognition system for neural network detection and made improvements, and compared it with various improved neural network detection systems [16] [17] through experiments. An improved method for driver behavior recognition has been proposed, in which unsafe driving behaviors of drivers will be monitored and alarmed in real time. Feng et al. designed a method to determine driver behavior through human body position movements. By improving traditional limb positioning methods, the detection speed of driver behavior can be improved, and the feedback to the human body model can be more accurate [18]. Knapik and Cyganek proposed a new method for driver fatigue recognition based on thermal imaging yawn detection [19]. This method is integrated with an active driving assistance system, which meets real-time monitoring requirements and can alert drivers of irregular behavior. Tran et al. designed a detection scheme to detect driver distracted driving behavior, which identifies distracted driving behavior by observing the driver's camera [20]. Implement deep convolutional neural network for driver anomaly detection on the embedded end, and after computer vision processing, detect abnormal behavior. When the driver experiences abnormal behavior, record and alarm. Eraqi proposed a driver detection scheme based on deep learning [21], which is implemented by an improved neural network structure, using segmented facial features, hand position movements, and skin positions to detect and analyze changes in the driver analysis process.

The detection method based on facial image information has the characteristics of strong objectivity, high convenience, low cost, and easy implementation. When abnormal situations occur during driving, facial features will undergo significant changes. Machine learning allows this method to quickly locate and recognize facial features and respond to driver behavior in real-time. With the continuous advancement of image processing technology, this method has become a mainstream method for detecting abnormal driving behavior. However, during the detection process, the impact of changes in external light and obstacles reduces the detection accuracy.

## **2.3 Fatigue driving behavior detection based on vehicle data**

The detection method based on vehicle status information refers to the detection of vehicle speed, acceleration, vehicle rotation angle, and other information based on

---

the driver's driving behavior. McDonald et al. designed and evaluated algorithms that can be used to detect driver drowsiness [22]. This algorithm judges the steering angle, throttle opening and closing, and vehicle speed changes in vehicle data. By combining these detection data with the network to determine the relationship between the data, this method explains the temporal variation between fatigue levels. Al Libawy et al. proposed a new modular design method for detecting and warning driver fatigue systems, using a particle swarm optimization algorithm to optimize this design scheme [23]. Chen et al. proposed a graphical detection method for detecting driver behavior to analyze driver behavior [24]. Determine the fixed driving style of drivers based on their long-term driving habits and then classify them to form specific driving habits. This can vividly explain the characteristics of each driver and record and analyze them. Hwang et al. have long extensively collected and recorded the dynamic vehicle information flow of the OBD port and established a big data mechanism for driver behavior data mining [25]. Calculate the number of occurrences of driving behavior in each driving route for a shortcut, analyze the driving style, and finally, use a decision model to analyze the driver's behavior. Lee and Jang studied a large amount of driving data and established a model for classifying potential abnormal driving behavior as a judgment for driving behavior [26]. Yao et al. constructed a driver behavior judgment and fuel consumption prediction model [27]. Martinelli et al. obtained vehicle data from the CAN bus to describe current driving behavior and used decision tree algorithm training to determine whether the current driving behavior was the same as before to improve driving safety [28].

A detection method based on vehicle motion characteristics analyzes vehicle data in motion (including speed, acceleration, yaw angle, etc.) to determine the driver's behavior controlling the vehicle, thereby indirectly determining whether the driver is in an abnormal state. This method does not require direct contact with the driver, and the feature extraction method is relatively direct and has a fast detection speed. However, vehicle data heavily relies on individual driving habits, making it difficult to determine different road conditions. Thus the robustness of this method is not high.

## **2.4 Fatigue driving behavior detection based on information fusion**

Due to significant performance differences between drivers, error detection may occur based on a detected feature. Therefore, the accuracy of judging abnormal driving of drivers based on individual features is not high. Drivers have different driving

---

characteristics, such as frequent blinking, yawning, frequent changes in throttle switch, and deeper vehicle deviation. To comprehensively analyze the relationship between these features and driver status, Al Libawy has proposed an information fusion method to detect abnormal driving behavior [29]. Real-time monitoring of driver fatigue status is achieved by obtaining vehicle acceleration and steering angle feature information from the natural environment and using machine vision to detect driver body movements and facial feature information for information fusion. Liu et al. proposed a scheme for integrating driving data (SAX-DF) and analyzed the correlation between factors, considering various influencing factors to predict and judge driving behavior [30]. Based on the comprehensive evaluation theory, Ma et al. proposed a driving behavior evaluation system that combines four indicators: eye-opening and closing, electromyography (EMG), electrocardiogram (ECG), and grip strength [31]. Standardize the design of various indicators and propose a fatigue evaluation system. Zhang et al. analyzed the differences between single-mode and multimodal detection methods by detecting the fatigue status of drivers through human body indicators, EEG, and images. They proposed a fusion of facial fatigue and multimodal information, greatly improving the accuracy and robustness of detection [32]. Xinyue et al. proposed a fatigue detection scheme based on multi-source information fusion. They compared it with other single detection methods to compare the facial features, driving characteristics, and physiological information detection methods of drivers, demonstrating the superiority of this detection scheme [33]. Lu et al. proposed a color image recognition method that combines key point action features with head swing and hand movements, designs an action detection model to improve recognition accuracy, and utilizes key point action localization to detect driving behavior [34]. Khodai ry and Abosamra use LSTM models to determine abnormal driving behavior, classify and monitor it through deep learning networks, and transmit it to mobile devices for implementation. Mobile detection improves speed and accuracy [35]. Jia et al. designed a driver facial feature detection system (FFD system) and a driver fatigue state judgment algorithm (MF algorithm) [36]. Combined with these parameters, the frequency and number of head swings can comprehensively assess the driver's fatigue state.

Traditional single-input detection methods have their advantages and disadvantages. Because driving behavior is a complex physiological and psychological phenomenon, a single-channel fatigue index cannot accurately reflect driving status.

---

The information extraction process is unstable due to external interference. Therefore, fatigue driving detection methods based on a single information source is unreliable. To ensure real-time detection accuracy, detection methods based on information fusion are becoming increasingly popular. The information source layer in the classification process includes the raw data, feature extraction, and classification decision layers. The level of information fusion can be divided into three levels: data-level information fusion, feature-level information integration, and decision-level information integration.

### **3. Research Methods**

#### **3.1 Driver Fatigue Feature Extraction**

When drivers carry out daily work, using image information collection and vehicle data access has a high degree of objectivity and robustness. However, when using physiological feature detection, users are highly invasive and susceptible to external interference, which affects the driver's driving experience and is not conducive to safe driving. Therefore, for the driving behavior of heavy trucks, the fusion of facial information and vehicle data is used to detect abnormal driving behavior.

##### **3.1.1 Method for Extracting driver's facial features**

Design a method to extract the facial key point positions of drivers. After facial detection and eye localization work, propose and implement facial feature extraction of facial key point positions. Firstly, obtain the edge positions of the facial parts, and then obtain the degree of opening and closing and aspect ratio from the edge points of the eyes and mouth, respectively. This method is used to obtain facial features of the driver's eye opening and closing degree and the degree of opening and closing times from facial image information of drivers under different driving fatigue states.

Firstly, recognize the facial features of the driver, including the contour features of key points in various parts. Secondly, the extracted features are used to locate key point positions through a regressor; At this point, generate the positions and actions of facial feature key points from its original image. Then, use the detection network [37] to adjust the feature position action and continuously improve the similarity with the real situation; Calculate the regression coefficients for each stage using the least squares

method. Figure 1 is a location map of 68 feature key points in the face.

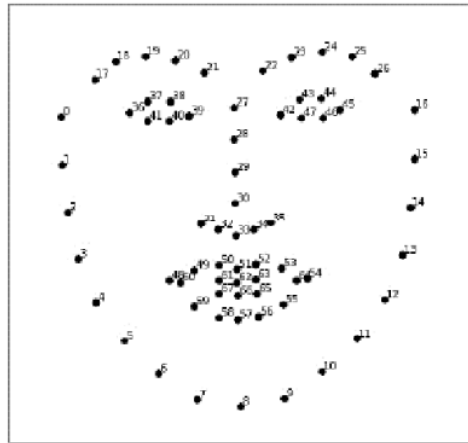


**Figure 1 68 feature points of the face**

The partial detection algorithm is implemented using Dlib, and its positioning detection principle is to determine the position through a decision model [38]. It has the advantage of computational speed, usually for the purpose of real-time monitoring when detecting faces, locating facial feature positions only takes 1 millisecond.

The positioning position of human eye feature points varies with the changes in human eye state on the plane display, so the driver's eye state can be represented by locating the human eye position. The position points of the left eye are numbered from 37 to 42; The position points of the right eye are numbered from 43 to 48. Soukupov á et al. [39] first proposed the Eye Aspect Ratio (EAR) in 2016. The EAR value can be calculated by accurately locating 68 key feature points on the face. Compared with the EAR value when the eyes are normal, it can determine the degree of eye opening and closing, and achieve real-time detection of blinking. The human eye detection points shown in Figure 2.



**Figure 2 Distribution of 12 feature points of the human eye**

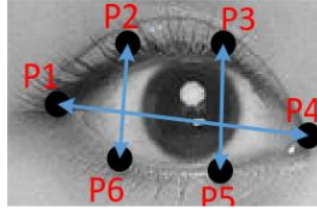


**Figure 3 EAR definition**

The P1~P6 and EAR in the human eye position points in Figure 3 can be obtained by the following formula:

$$EAR = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2\|P_1 - P_4\|}$$

Calculate the EAR value based on the ratio of the vertical and horizontal features of the human eye.

Yawning is a noticeable manifestation of the driver's mouth during fatigue driving. In this case, the degree of opening and closing of the mouth is greater than the distance when smiling or speaking, and the lateral distance of the mouth significantly decreases. Therefore, MAR can be used to quantitatively analyze the opening and closing of the mouth. Based on the ERT algorithm, there are 20 oral feature points with sequence numbers ranging from 49 to 68. When the mouth performs different actions, its position points will change with the action, and MAR can represent changes in facial expressions. Therefore, driver fatigue status can be extracted based on oral feature points.

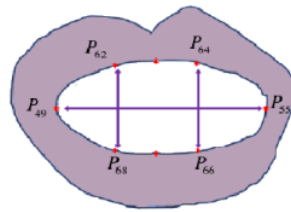


**Figure 4 The distribution of 6 feature points in the mouth**

P46~P68 in Figure 3.15 correspond to the position points of the oral cavity, and the formula for MAR is:

---


$$MAR = \frac{\|P_{62} - P_{68}\| + \|P_{64} - P_{66}\|}{2\|P_{49} - P_{55}\|}$$

### 3.1.2 Research on Abnormal Driving Data of Vehicles

Among the various influencing factors of fatigue driving, the factors of the vehicle itself and the road environment cannot be changed during vehicle driving. Therefore, to improve fatigue driving, research should mainly focus on the driver's own factors. Therefore, using the collected operational data of trucks under natural driving, data preprocessing is first carried out to define relevant concepts, laying the foundation for analyzing parameters such as truck driving time and average speed and mining parameters related to truck driver fatigue driving.

The process of data processing and analysis is as follows: first, preprocess the data and define parameters such as driving time, rest time, driving behavior occurrence time, and danger occurrence; Use statistical analysis methods to calculate the distribution of two parameters and determine vehicle information parameters for judgment fusion analysis.

Data preprocessing is the first step in data analysis, mainly including data cleaning, conversion, and other operations. Based on the research purpose, this article retains the vehicle ID, time, speed, system alarms, braking force, brake pedal status, heading angle, vehicle speed, roll angle, lateral acceleration, longitudinal acceleration, and current position of each truck.

### 3.2 Fatigue driving detection method based on multi-source information fusion

The detection of fatigue driving behavior adopts a multi-information fusion method, usually using a combination weighting method to weight feature attributes. Such models detect each other independently in time series, and it is difficult to identify the recovery process after fatigue behavior occurs, which can easily lead to misjudgment. Therefore, although there have been good achievements and progress in recognition research based on information fusion, there are still many directions for

---

improvement in recognition methods. Therefore, deep learning-based information fusion detection methods have important research significance and value, whether in academia or in practical applications.

Information fusion refers to the comprehensive processing of information from multiple similar or heterogeneous information sources, used for preprocessing, data registration, prediction and estimation, and arbitration decision-making, to obtain more accurate, stable, and reliable target information than a single information source. Information fusion is consistent with how humans perceive the external environment, obtaining external environmental information through various senses such as vision, hearing, smell, and touch. Then, the brain comprehensively analyzes various information and ultimately makes judgments about the external environment. The final decision result is obtained through the fusion of decision layers.

Multi-source information has two main characteristics: (1) Information complementarity. The complementarity of information enhances its coverage and further enhances its richness. Based on richer multi-source information, target information can be perceived more comprehensively and accurately. (2) Information redundancy. The redundancy of information improves the system's fault tolerance ability, thereby enhancing the system's stability. Based on redundant information, the system is more resistant to interference from various information sources.

Information fusion is mainly carried out from the following three levels:

(1) Data layer fusion. Data layer fusion is the fusion of raw data from different aspects. The premise of data layer fusion is the isomorphism of multi-source information. When the physical meanings of multi-source information are similar, and the data dimensions are similar, data layer fusion of multi-source information can be carried out. Data layer fusion belongs to the lowest level of information fusion. Its advantage is that it retains all the original information. Still, its disadvantage is that compared to other methods, it has a larger amount of data, which can easily cause data congestion and poor real-time performance.

(2) Feature layer fusion. Feature level fusion refers to preprocessing and feature extraction after obtaining various raw data and then fusing the features of each information source to further obtain prediction and estimation of target information. The key to feature layer fusion is to extract the features of the original data and extract features that can represent the target information from each information source, thereby greatly reducing the amount of data.

---

(3) Decision layer integration. Decision level fusion refers to making decisions on the single target information of each information to determine data features, obtaining single local decisions, associating and judging the single local decisions of each information source, and transmitting them to the fusion model to generate results.

Various information sources can reflect the driver's fatigue level from different perspectives in the scene of driving fatigue detection. Driver facial image information, physiological information such as EEG, ECG, and EMG, driving behavior information, and vehicle driving information are commonly used for driving fatigue detection. Among them, the driver's facial information and the vehicle's driving characteristics are heterogeneous and complementary. For this multi-source heterogeneous information, data layer fusion is usually not used.

## **4. Research Content**

### **(1) Research objectives**

We constructed a dataset of driving behavior and obtained effective and feature-rich enhanced samples through sample-based data augmentation methods. Due to the detection target's wide variety and span of data, a decision model is planned to be used for decision-level information fusion. While improving the reliability of fatigue-driving behavior judgment, the results of the neural network layer are continuously adjusted through input data to better capture fatigue. Driving characteristics. Using a cascaded network architecture, fatigue driving behavior can be judged accurately and quickly while avoiding false detections caused by external interference. Finally, the facial features of the driver and vehicle data were integrated.

### **(2) Research content**

- 1) Research on driver fatigue feature extraction methods.
- 2) Research on Vehicle Fatigue Driving Data.
- 3) Fatigue driving behavior judgment based on multi-source information fusion.
- (3) Key issues to be addressed

In information fusion, the dimension span of vehicle features and driver feature data is relatively large, and universal information fusion models are ineffective in detecting fatigue driving behavior. Due to the recovery of tired driving behavior to normal driving, the moment of sleepy driving behavior is included, which leads to the model making incorrect judgments and interfering with data analysis.

---

## 5. Excepted Results

### (1) Research methods

1) Literature retrieval methods, relevant information retrieval, summarizing the research status, technical implementation methods, difficulties encountered, and research deficiencies in the relevant fields of this topic.

2) The block-based research method divides the functions involved in the research content into image correction algorithm research, fatigue driving behavior recognition model research based on information fusion, and driver rating model research based on data analysis. According to the characteristics of each module, different research methods are adopted.

3) Comparative analysis method, based on existing research results and actual data, conducted comparative experiments on multiple factors and compared the detection results of the designed deep learning model with traditional object detection models.

### (2) Expected results

A dataset of fatigue driving behavior was constructed, and effective and feature-rich detection samples were obtained through adaptive image correction. Due to the large-scale span of targets in the target dataset and the significant interference impact, it is planned to detect fatigue driving behavior based on multi-source information fusion. While ensuring detection accuracy, it improves the speed and robustness of the detection system, thereby accurately extracting the driving behavior characteristics of the driver. By fusing vehicle data and facial features to determine driver fatigue driving behavior, fatigue driving behavior can be accurately and quickly detected while effectively avoiding false detection caused by background.

## 6. Evaluation

The main purpose of this article is to fuse the heart rate and facial features of drivers who are in a state of fatigue during driving, and input the obtained fusion features into a decision model to determine the degree of fatigue.

The research topic of this article still needs to be continuously improved and perfected in practical applications, and further expands research and development breakthroughs in the following areas:

### (1) Driver image information collection

Contactless collection methods will become a future research and development trend. Under low light conditions, it is difficult to recognize contours when detecting abnormal driving behavior based on facial features. Due to commonly used data correction methods to enhance the overall image, poor pertinence, loss of image details, and difficulty in accurately detecting real-time feedback of driver status, resulting in low detection model accuracy

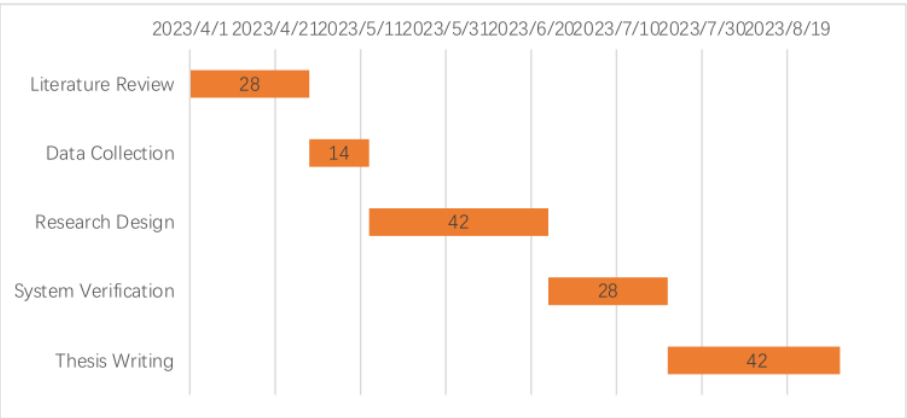
(2) Dataset

The dataset for simulating driving experiments in this article is relatively small, and the range and representativeness of the vehicle and facial fusion feature dataset are insufficient. The national recognition has a greater impact, fully making the dataset reasonable and reliable.

(3) Design Decision Model Network

In the future, neural network optimization algorithms can be used to optimize network structure and parameter training to improve the recognition accuracy of models. For example, using the momentum method, which is the exponentially weighted moving average method; Adaptive Learning Rate Adjustment (RMSProp); Adaptive Momentum Estimation (Adam) uses momentum as the parameter update direction and can also adjust the learning rate.

Gantt chart



---

## References

- |                                                                                                                                                                                                                                                                                                                                       |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [1] Cheah, C. S. (2020). Factors contributing to the difficulties in teaching and learning Amodio, A., Ermidoro, M., Maggi, D., Formentin, S., & Savaresi, S. M. (2018). Automatic detection of driver impairment based on pupillary light reflex. <i>IEEE transactions on intelligent transportation systems</i> , 20(8), 3038-3048. |
| [2] Ali Y, Sharma A, Haque M M, et al. The impact of the connected environment on driving behavior and safety: A driving simulator study[J]. <i>Accident Analysis &amp; Prevention</i> , 2020, 144: 105643.                                                                                                                           |
| [3] Abou El Assad Z E, Mousannif H, Al Moatassime H, et al. The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review[J]. <i>Engineering Applications of Artificial Intelligence</i> , 2020, 87: 103312.                                                |
| [4] Babaeian M, Mozumdar M. Driver drowsiness detection algorithms using electrocardiogram data analysis[C]//2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC). IEEE, 2019: 0001-0006.                                                                                                                  |
| [5] Nemcova A, Svozilova V, Bucsuházy K, et al. Multimodal features for detection of driver stress and fatigue[J]. <i>IEEE Transactions on Intelligent Transportation Systems</i> , 2021, 22(6).                                                                                                                                      |
| [6] Haghani M, Bliemer M C J, Farooq B, et al. Applications of brain imaging methods in driving behaviour research[J]. <i>Accident Analysis &amp; Prevention</i> , 2021, 154: 106093.                                                                                                                                                 |
| [7] Tian Y, Cao J. Fatigue driving detection based on electrooculography: a review[J]. <i>EURASIP Journal on Image and Video Processing</i> , 2021, 2021(1): 1-17.                                                                                                                                                                    |
| [8] Gu X, Zhang L, Xiao Y, et al. Non-contact fatigue driving detection using CW Doppler radar[C]//2018 IEEE MTT-S International Wireless Symposium (IWS). IEEE, 2018: 1-3.                                                                                                                                                           |
| [9] Purnamasari P D, Yustiana P, Ratna A A P, et al. Mobile EEG based drowsiness detection using K-nearest neighbor[C]//2019 IEEE 10th International Conference on Awareness Science and Technology (iCAST). IEEE, 2019: 1-5.                                                                                                         |

|                                                                                                                                                                                                                                                      |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [10]Caryn F H, Rahadiani L. Driver Drowsiness Detection Based on Drivers' Physical Behaviours: A Systematic Literature Review[J]. Computer Engineering and Applications Journal, 2021, 10(3): 161-175.                                               |
| [11]Li K, Gong Y, Ren Z. A fatigue driving detection algorithm based on facial multi-feature fusion[J]. IEEE Access, 2020, 8: 101244-101259.                                                                                                         |
| [12]Zhang L, Tian X, Jiang W, et al. A Facial Fatigue Expression Recognition Method Based on Sparse Representation on the Low-Resolution Image[C]//International Conference on Machine Learning for Cyber Security. Springer, Cham, 2020: 269-278.   |
| [13]Ji Y, Wang S, Zhao Y, et al. Fatigue state detection based on multi-index fusion and state recognition network[J]. IEEE Access, 2019, 7: 64136-64147.                                                                                            |
| [14]Ye Z, Wu Q, Zhao X, et al. Abnormal Driving Detection Based on Human Pose Estimation and Facial Key Points Detection[C]//International Conference on Intelligent Computing. Springer, Cham, 2021: 91-102.                                        |
| [15]Mumcuoglu M E, Alcan G, Unel M, et al. Driving behavior classification using long short term memory networks[C]//2019 AEIT International Conference of Electrical and Electronic Technologies for Automotive (AEIT AUTOMOTIVE). IEEE, 2019: 1-6. |
| [16]Xing Y, Lv C, Wang H, et al. Driver activity recognition for intelligent vehicles: A deep learning approach[J]. IEEE transactions on Vehicular Technology, 2019, 68(6): 5379-5390.                                                               |
| [17]Zhang Y, Li J, Guo Y, et al. Vehicle driving behavior recognition based on multi-view convolutional neural network with joint data augmentation[J]. IEEE Transactions on Vehicular Technology, 2019, 68(5): 4223-4234.                           |
| [18]Zhang C, Lu Y, Feng M, et al. Trucker behavior security surveillance based on human parsing[J]. IEEE Access, 2019, 7: 97526-97535.                                                                                                               |
| [19]Knapik M, Cyganek B. Driver's fatigue recognition based on yawn detection in thermal images[J]. Neurocomputing, 2019, 338: 274-292.                                                                                                              |

|                                                                                                                                                                                                                                                         |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [20] Tran D, Manh Do H, Sheng W, et al. Real-time detection of distracted driving based on deep learning[J]. IET Intelligent Transport Systems, 2018, 12(10): 1210-1219.                                                                                |
| [21] Eraqi H M, Abouelnaga Y, Saad M H, et al. Driver distraction identification with an ensemble of convolutional neural networks[J]. Journal of Advanced Transportation, 2019, 2019.                                                                  |
| [22] McDonald A D, Lee J D, Schwarz C, et al. A contextual and temporal algorithm for driver drowsiness detection[J]. Accident Analysis & Prevention, 2018, 113: 25-37.                                                                                 |
| [23] Al-Libawy H, Al-Ataby A, Al-Nuaimy W, et al. Modular design of fatigue detection in naturalistic driving environments[J]. Accident Analysis & Prevention, 2018, 120: 188-194.                                                                      |
| [24] Chen C, Zhao X, Zhang Y, et al. A graphical modeling method for individual driving behavior and its application in driving safety analysis using GPS data[J]. Transportation research part F: traffic psychology and behaviour, 2019, 63: 118-134. |
| [25] Hwang C, Chen M S, Shih C M, et al. Apply Scikit-learn in python to analyze driver behavior based on OBD data[C]//2018 32nd International Conference on Advanced Information Networking and Applications Workshops (WAINA). IEEE, 2018: 636-639.   |
| [26] Lee J, Jang K. A framework for evaluating aggressive driving behaviors based on in-vehicle driving records[J]. Transportation research part F: traffic psychology and behaviour, 2019, 65: 610-619.                                                |
| [27] Yao Y, Zhao X, Zhang Y, et al. Modeling of individual vehicle safety and fuel consumption under comprehensive external conditions[J]. Transportation research part D: transport and environment, 2020, 79: 102224.                                 |
| [28] Martinelli F, Mercaldo F, Orlando A, et al. Human behavior characterization for driving style recognition in vehicle system[J]. Computers & Electrical Engineering, 2020, 83: 102504.                                                              |

|                                                                                                                                                                                                                                                            |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [29]Al-Libawy H, Al-Ataby A, Al-Nuaimy W, et al. Modular design of fatigue detection in naturalistic driving environments[J]. Accident Analysis & Prevention, 2018, 120: 188-194.                                                                          |
| [30]Liu J, Li T, Yuan Z, et al. Symbolic aggregate approximation based data fusion model for dangerous driving behavior detection[J]. Information Sciences, 2022, 609: 626-643.                                                                            |
| [31]Ma Z, Yao S, Zhao J, et al. Research on Drowsy-driving Monitoring and Warning System Based on Multi-feature Comprehensive Evaluation[J]. IFAC-PapersOnLine, 2018, 51(31): 784-789.                                                                     |
| [32]Zhang M, Zhao B, Tang J, et al. Research on tiredness detection method based on fusion of face image and EEG information[C]//2021 IEEE 3rd International Conference on Frontiers Technology of Information and Computer (ICFTIC). IEEE, 2021: 396-400. |
| [33]Xinyue J, Ming J, Hui S, et al. Research on Fatigue Driving State based on Multi-source Information Fusion[J]. 2019.                                                                                                                                   |
| [34]Lu M, Hu Y, Lu X. Pose-guided model for driving behavior recognition using keypoint action learning[J]. Signal Processing: Image Communication, 2022, 100: 116513.                                                                                     |
| [35]Khodairy M A, Abosamra G. Driving behavior classification based on oversampled signals of smartphone embedded sensors using an optimized stacked-LSTM neural networks[J]. IEEE Access, 2021, 9: 4957-4972.                                             |
| [36]Jia H, Xiao Z, Ji P. Real-time fatigue driving detection system based on multi-module fusion[J]. Computers & Graphics, 2022, 108: 22-33.                                                                                                               |
| [37]Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. Annals of statistics, 1189-1232.                                                                                                                                   |
| [38]Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). Imagenet classification with deep convolutional neural networks. Communications of the ACM, 60(6), 84-90.                                                                                       |

---

[39]Cech, J., & Soukupova, T. (2016). Real-time eye blink detection using facial landmarks. Cent. Mach. Perception, Dep. Cybern. Fac. Electr. Eng. Czech Tech. Univ. Prague, 1-8.

FINAL GRADE

GENERAL COMMENTS

Instructor

65/100

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17

GRADING FORM: ACFA7004\_SEMB\_2023

HAOZHE ZHANG

65

**ENGAGEMENT WITH LITERATURE**

*(20 marks)*



Included references are thematically relevant and used in support of proposal presented ideas very well.

15

**KNOWLEDGE AND UNDERSTANDING**

*( 20 marks)*



Fatigue driving and algorithms that can aid this research area are explored in some depth. In so doing a firm rationale for future research has been established.

14

**COGNITIVE/ INTELLECTUAL SKILL**

*(30 marks)*



Very limited information included for your research methodology.

**13**

#### **PRACTICAL/ APPLICATION SKILLS**

*( 10 marks)*



Listed problems are planned for very well.

**12**

#### **TRANSFERRABLE SFL/ PP**

*( 20 marks)*



**11**