Dean&Francis

ISSN 2959-6157

Monitoring Pilot Driving Status based on Facial Features and Physiological Signals under a Single-pilot Flight Mode

Jingfei Ai[1, *]

[1]School of information and Communication Engineering, Hainan University, Haikou, 570000, China

*Corresponding author: 20233006393@hainanu.edu.cn

Abstract:

This paper systematically reviews pilot state monitoring technologies based on facial features and physiological signals under the Single Pilot Operations (SPO) mode. The SPO mode replaces the traditional two-pilot interpersonal coordination with a 'human-machine-ground' collaboration, which can reduce crew costs and fuel consumption, but relies on technical monitoring to fill the gap of 'interpersonal supervision.' The study summarizes the core principles and indicators of facial feature monitoring and physiological signal monitoring, analyzes the performance of multimodal data fusion methods, machine learning, and deep learning models in state recognition, and validates the role of multimodal fusion in improving recognition accuracy through related research findings. Current technologies face challenges such as facial occlusion, insufficient comfort in physiological signal acquisition, lack of data privacy, poor model generalization, and inconsistent industry standards. Future efforts should optimize device design and strengthen interdisciplinary collaboration to promote standardization, thereby facilitating the practical application and adoption of SPO monitoring technologies.

Keywords: Single Pilot Operation (SPO); Driving Status Monitoring; Facial features; Physiological signals; Multimodal data fusion.

1. Introduction

In recent years, the global aviation industry has shown a trend toward higher efficiency and lower costs. The single pilot operation (SPO) mode has gradually become an important development direction in the field of air transportation, as it can reduce crew requirements, lower operating costs (such as fuel consumption and personnel training costs), and optimize the allocation of route resources. The SPO mode can significantly improve the operational efficiency of small and medium-sized passenger and cargo flights by restructuring cockpit collaboration mechanisms and flight process organization. Howev-

ISSN 2959-6157

er, it also places higher demands on pilots' continuous safe operation capabilities — the traditional two-pilot model's mechanism of 'mutual supervision and collaborative decision-making' is absent, significantly increasing safety risks caused by human errors (such as fatigue, distraction, and stress responses) [1].

According to aviation safety data, human factors account for more than 70% of aviation accident causes, and under the SPO mode, the pilot's physiological and psychological state directly determines flight safety. By real-time monitoring of driving status through facial features (such as blink frequency, eye movement trajectories) and physiological signals (such as EEG, heart rate variability), risks such as fatigue and inattention can be alerted promptly. This is a core technological support for the large-scale implementation of the SPO mode [1]. In existing research on driver fatigue detection, related results have achieved high-precision detection by integrating heart rate and facial features [2], reduced false detection rates of single features by combining heart rate variability and facial key point features [3], and verified the sensitivity of physiological signals to fatigue states by leveraging multiple types of physiological signals [4]. These technical approaches provide important references for pilot status monitoring under the SPO mode, but targeted adaptive optimization is needed for the particular environments of pilot cockpits, such as complex lighting and confined spaces, as well as the task characteristics of long-term concentration and high stress [2-4].

In addition, smart cushions integrating MEMS and optical sensors can achieve real-time collection of heart rate and respiratory rate without interfering with driving operations. The optimized sensor layout provides a reference for the design of physiological signal acquisition devices in SPO cockpits [5]. By combining wireless ECG sensor patches with cameras, it was found that specific ratios in heart rate variability are highly correlated with yawning frequency, providing new evidence for multi-indicator collaborative assessment of pilot fatigue in SPO conditions [6]. Remote photoplethysmography (rPPG) technology can non-contactly extract physiological signals such as heart rate and respiratory rate through existing cockpit cameras, offering a technical direction to address sensor-wearing interference in SPO scenarios [7]. Meanwhile, in facial feature monitoring, a combination of multi-task convolutional neural networks (MTCNN) and ensemble regression trees (ERT) can achieve stable tracking of pilots' facial key points, ensuring feature extraction accuracy even with head pose changes [3]. In terms of physiological signal processing, wavelet transform denoising technology can effectively reduce cockpit vibration interference on signals such as ECG and galvanic skin response (GSR), improving signal quality [8,9]. For stress state monitoring, sudden changes in GSR signals can quickly reflect pilot emotional fluctuations, supporting early warning of status under sudden failures [8].

This study aims to provide a comprehensive review of research progress in driver state monitoring based on facial features and physiological signals under SPO (Single Pilot Operations) mode. It systematically summarizes the principles of monitoring technologies, evaluation models, and applications, analyzes current research limitations, and offers directions for future technological breakthroughs. Specifically, it is necessary to investigate the monitoring effectiveness of facial features (such as PERCLOS, blink frequency, head posture) and physiological signals (such as EEG, ECG, GSR) under SPO mode, and to clarify whether different signals differ in their ability to represent pilot fatigue, attention distraction, and stress states. Additionally, the study should examine the fusion effects of multimodal monitoring technologies and explore how feature-level or decision-level fusion can address the problem of single signals being easily interfered with (e.g., facial features affected by lighting conditions, physiological signals affected by motion noise), while also considering whether the experience of the multi-stage attention network (NMSNet) proposed by Li Jing [9] in integrating EEG, peripheral physiological signals, and facial expressions can be transferred to the SPO scenario. Furthermore, it is necessary to analyze the generalization capabilities of existing evaluation models (such as traditional machine learning and deep learning) in the SPO context, and determine how models should balance accuracy and real-time performance in consideration of individual pilot differences (e.g., differing baseline physiological signals) and dynamic tasks (e.g., takeoff, cruise, landing).

This study focuses on driver state monitoring in the SPO (Single Pilot Operation) model based on facial features (such as eye openness) and physiological signals (such as heart rate), with an emphasis on techniques for assessing pilot fatigue, attention, and other states. It covers the fusion of multi-source features, intelligent algorithms, and the analysis of the effectiveness and limitations of monitoring technology in complex environments. Methods such as literature retrieval, analysis, induction, and summary are employed to review relevant literature, integrate research findings, and summarize key technologies, algorithm characteristics, and development trends, providing a reference for the development of this field.2 Overview of the Single Pilot Driving Mode.

2. Overview of Single-Pilot Operation Mode

2.1 The Concept and Characteristics of the SPO Model

SPO mode refers to a 'flight mode led by a single pilot, with the flight task accomplished through assistance from ground coordination systems and cockpit automation equipment for flight planning, fault diagnosis, and emergency handling.' Its core is the 'human-machine-ground' collaboration, which replaces the traditional interpersonal coordination between two pilots.

Compared with the traditional two-pilot model, the SPO mode differs in multiple aspects. In terms of crew configuration, the traditional model clearly divides responsibilities between the captain and the co-pilot, whereas the SPO mode involves a single pilot supported by ground control, requiring the pilot to handle both decision-making and operations. Regarding operational costs, the traditional model incurs higher costs due to personnel training, salaries, and fuel consumption, while the SPO mode can reduce crew costs by 50% and decrease fuel consumption by 8%-12%. In terms of decision-making processes, the traditional model relies on two-way communication confirmation with a high tolerance for errors, whereas the SPO mode is predominantly one-way with ground support, leading to higher decision-making efficiency but dependence on monitoring and early warning systems. Regarding safety reliance, the traditional model depends on human supervision, such as co-pilots warning of fatigue, whereas the SPO mode relies on technological monitoring, including physiological signal alerts and automated error correction.

The safety of SPO mode is highly dependent on the stability of the pilot's condition: prolonged flights can lead to fatigue (during the cruising phase), sudden malfunctions can trigger stress responses (such as engine failure), and a single operational link can result in errors due to attention lapses (such as accidentally pressing control buttons). Therefore, real-time monitoring technology is needed to fill the gap of 'human supervision'.

2.2 The Current Status and Trends of SPO Model Development

The current SPO (Single Pilot Operations) mode has entered the stage of technical testing and regulatory exploration: companies such as Airbus and Boeing are testing the SPO mode on cargo flights like the Boeing 777F, relying on cockpit automation systems such as automatic landing and fault self-diagnosis to reduce pilot workload; the SPO verification system built by Wang Miao and others has also achieved simulated flights for short domestic regional routes [1]. On the regulatory side, the International Civil Aviation Organization (ICAO) has not yet issued a unified certification standard, with only the European Union Aviation Safety Agency (EASA) releasing the 'SPO Safety Assessment Guide' in 2022, which explicitly requires that the accuracy of monitoring system status recognition be no less than 92%. However, technical bottlenecks remain significant. Existing monitoring technologies are mostly adapted from ground driving and have not been optimized for cockpit microenvironments such as low light and high vibration, resulting in issues like poor signal acquisition stability and insufficient model generalization capability.

In the future, the SPO model will advance toward intelligence, lightweight design, and standardization: In terms of intelligent monitoring, by integrating facial, physiological, and operational data and utilizing deep learning models such as NMSNet proposed by Li Jing, an integrated framework of 'state recognition - risk warning - decision support' can be realized [9]; at the equipment level, non-invasive physiological signal acquisition devices such as integrated EEG headsets and flexible electrodermal sensors will be developed to avoid interfering with pilot operations; at the regulatory and standards level, the establishment of industry standards for SPO monitoring systems will be promoted, clarifying data privacy protection requirements such as the scope of signal acquisition and encrypted transmission of physiological signals, as well as standardizing early warning indicators such as fatigue PERCLOS thresholds.

3. Pilot Facial Feature and Physiological Signal Monitoring Technology

3.1 Facial Feature Monitoring Technology

3.1.1 Principles and methods

Pilot facial feature monitoring based on computer vision and image processing technology involves collecting images or videos of the pilot's face by deploying devices such as RGB-D cameras and infrared cameras inside the cockpit. The process follows the core workflow of 'face detection - keypoint localization - feature extraction' to obtain state representation indicators. Specifically, a multi-task convolutional neural network (MTCNN) is first used to accurately annotate the face bounding box, and then 68 facial keypoints are located using an ensemble of regression trees (ERT). This approach ensures stable tracking even when the pilot turns their head to check instruments or other head pose changes. Subsequently, based on the

ISSN 2959-6157

keypoint coordinates, dynamic features such as eye aspect ratio (EAR), mouth aspect ratio (MAR), and head deflection angle are calculated. These features can intuitively reflect the pilot's blinking state, yawning behavior, and level of attention, providing critical information for subsequent assessment of driving states.

3.1.2 Main monitoring indicators and status correlation

Driving state monitoring involves various indicators, each with different calculation methods and associations with driving conditions. Blink frequency is calculated by counting the number of blinks within a certain period; a frequency greater than 20 times per minute or less than 5 times per minute indicates distracted attention or fatigue [2]. PERCLOS is calculated as the proportion of time within a unit period during which the eyelid covers more than 80% of the pupil area; if PERCLOS is greater than 0.25, it is considered moderate fatigue, and if greater than 0.4, severe fatigue [2,10]. The Eye Aspect Ratio (EAR) is the ratio of vertical eye distance to horizontal eye distance; when EAR is less than 0.2 and the eyes remain closed for more than 1 second, it indicates fatigue [3]. The Mouth Aspect Ratio (MAR) is the ratio of the vertical mouth distance to the horizontal mouth distance; if MAR is greater than 0.5 and lasts for more than 2 seconds, it indicates yawning and suggests fatigue [3]. Head posture is measured by head tilt angles (such as pitch and yaw); if the tilt angle exceeds 30° and lasts for more than 3 seconds, it indicates distracted attention (such as looking at a phone) [2].

3.1.3 Examples of technology applications

In the technical practice of monitoring pilots' facial features, several representative solutions have demonstrated good adaptability. First, in a simulated cockpit environment, RGB-D cameras are used to capture videos of the pilot's face. With the aid of specific algorithms, heart rate signals can be effectively separated from facial image noise, and key indicators such as eye aspect ratio, mouth aspect ratio, and eyelid closure percentage can be extracted synchronously. Even under lighting variations in daytime and nighttime flights, the fatigue recognition accuracy remains relatively high, significantly outperforming traditional RGB cameras [2]. Second, specific facial recognition algorithms used in in-vehicle scenarios are transferred to the SPO cockpit for pilot facial keypoint localization. In simulated experiments, this approach yields high accuracy and low false detection rates for identifying the fatigue state of subjects. The algorithm shows notable improvements in adaptability compared to traditional solutions for pilots commonly wearing corrective glasses, effectively addressing feature extraction errors caused by equipment occlusion [3]. Additionally, remote photoplethysmography based on facial video can enhance signal-to-noise ratio by optimizing the selection of regions of interest, offering a new approach to address the occlusion problems caused by helmets and oxygen masks in SPO scenarios [7].

3.2 Physiological Signal Monitoring Technology

3.2.1 Principles and Methods

By collecting physiological or metabolic signals from pilots through non-invasive sensors, and performing signal preprocessing (filtering, denoising) and feature extraction, it is possible to reflect physiological and psychological states. Common physiological signals and their collection methods are as follows: Electroencephalography (EEG) is collected using non-invasive EEG headsets (such as Emotiv EPOC), which can record neuronal electrical activity on the scalp, reflecting cognitive load and fatigue [9]; Electrocardiography (ECG) is collected using flexible chest patch sensors, recording cardiac electrical activity to calculate heart rate (HR) and heart rate variability (HRV) [3]; Galvanic skin response (GSR) is collected through finger-worn sensors, measuring skin conductivity to reflect emotional stress responses (e.g., GSR increases during sudden malfunctions) [8]; Electromyography (EMG) is collected via facial EMG patches, recording electrical activity of facial muscles, reflecting tension (e.g., EMG amplitude of the forehead increases when frowning) [4]; respiratory rate and body temperature are collected using chest strap respirators and infrared thermometers, respectively. A respiratory rate above 25 breaths per minute indicates stress, and a body temperature above 37.5°C indicates physical discomfort [8].

3.2.2 Main monitoring indicators and status correlation

In the field of pilot physiological signal monitoring, different types of physiological signals can accurately reflect driving status through specific indicators. Among them, in electroencephalogram (EEG) signals, changes in the amplitude of specific frequency bands have clear significance: an increase in α waves (8-13Hz) indicates that the pilot is in a relaxed state, an increase in θ waves (4-7Hz) suggests fatigue, and an increase in β waves (14-30Hz) indicates an increased cognitive load [8,9]. In electrocardiogram (ECG) heart rate variability (HRV) indicators, a decrease in time-domain features such as MeanNN (average R-R interval) and SDNN (standard deviation of R-R interval) implies that the pilot may be under stress or fatigue. A frequency-domain feature, LF/HF (low frequency/high frequency power ratio) greater than 2, indicates sympathetic nervous system activation corresponding to a stress state [3,4]. In galvanic skin response (GSR), a sudden increase in skin conductance above 5μS indicates emotional fluctuations in the pilot (such as responding to emergencies), while sustained low conductance (less than 2μS) suggests fatigue [8]. In electromyography (EMG) signals, an EMG amplitude of the frontal muscles greater than 50μV indicates that the pilot is tense or highly focused, and frequent fluctuations in the masseter muscle EMG may indicate distraction (such as eating) [4].

Furthermore, by dynamically adjusting the weights of signals such as heart rate and respiration through an adaptive weighted fusion algorithm, its strategy for handling inconsistencies in multimodal data dimensions and noise interference can provide a reference for physiological signal fusion in SPO scenarios[5]. Actual road tests have found that combining differential LF/HF with yawning frequency can effectively classify fatigue levels. This multi-indicator collaborative approach can optimize the graded warning mechanism for pilot fatigue in SPO mode [6].

3.2.3 Examples of technology applications

At the specific technical application level, for monitoring pilots' cognitive load, some studies have developed a multimodal EEG monitoring scheme using the DEAP dataset, extracting channel, spatial, and temporal features of EEG through specialized networks, achieving a final recognition accuracy of 88.15%, significantly outperforming the traditional CNN model at 75.49% [9]. In a simulated SPO fatigue scenario, by collecting ECG, GSR, and respiration rate signals and using a random forest algorithm to integrate these features, a recognition accuracy of 94.72% and a recall rate of 90.58% were achieved [4]. In terms of stress state monitoring, a certain GSR-based stress monitoring scheme, in a simulated engine failure scenario, showed that the stress response delay of the GSR signal was less than 0.5 seconds, enabling 2-3 seconds of advance warning of the pilot's stress state, thus providing critical time for handling the failure [8].

4. Driver State Assessment Model Based on Facial Features and Physiological Signals

4.1 Data Fusion Methods

4.1.1 Feature layer fusion

In the feature-level fusion stage of multimodal data integration, facial features (such as eye aspect ratio and eyelid closure percentage) and physiological signal features (such as heart rate variability and EEG alpha wave amplitude) need to be standardized first. Then, they are fused through methods like vector concatenation or weighted averaging to retain the detailed information of the original features. The core advantage of feature-level fusion lies in its ability to fully utilize the complementarity of multimodal signals: facial features can intuitively reflect the pilot's external behavioral states (such as blink frequency and yawning as fatigue indicators), while physiological signals can accurately capture the pilot's internal physiological states (such as heart rate fluctuations indicating stress or fatigue). Combining both can effectively compensate for the susceptibility of single signals to interference, significantly reducing the false detection rate. In related practice, some studies use vector concatenation to fuse heart rate statistical features with facial features, then input them into a multimodal fusion recurrent neural network for training. Ultimately, the fatigue recognition accuracy increased by 5%-8% compared to single-feature detection, fully validating the effectiveness of feature-level fusion in improving monitoring accuracy.

4.1.2 Challenges and solutions of data fusion

Data fusion faces various challenges and corresponding solutions. In terms of inconsistent data dimensions, facial features are high-dimensional time-series data (e.g., 30 frames per second), whereas physiological signals are low-dimensional data (e.g., 1 sample per second). Zero-padding or interpolation methods can be used to unify the time-series length; for example, some studies interpolate heart rate data to 30 samples per second [2]. Regarding noise interference, cabin vibrations can introduce noise in physiological signals, and lighting changes can cause errors in facial features. Solutions include using wavelet transform to denoise physiological signals and using infrared cameras to reduce lighting effects on facial features [2, 9]. For feature weight imbalance, some features (such as EEG signals) are sensitive to states, while others (such as head pose) are less robust. Attention mechanisms can be introduced, such as the residual attention module in related studies, which can dynamically adjust feature weights [9].

4.2 Machine learning and deep learning models

4.2.1 Traditional machine learning model

Traditional machine learning models have different applications in scenarios such as driving state monitoring. Support Vector Machines (SVM) achieve linear classifi-

ISSN 2959-6157

cation by mapping to a high-dimensional space through kernel functions and are suitable for small-sample scenarios (such as SPO pilot experiments). In related studies, the accuracy reaches 91.84% [3]. The advantage is strong generalization ability, while the disadvantage is low training efficiency for large samples. Random Forests consist of multiple decision trees and make decisions through voting, making them suitable for multi-feature fusion scenarios. In related studies, the accuracy reaches 94.72% [4]. The advantage is resistance to overfitting, while the disadvantage is weak at capturing temporal features. Gradient Boosting Decision Trees (GBDT) improve classification accuracy by iteratively optimizing residuals, used for physiological signal feature classification. In related studies, the F1 score reaches 92.53% [3]. The advantage is high precision, while the disadvantage is susceptibility to outliers.

4.2.2 Deep learning model

In deep learning models for driving state assessment under the SPO mode, different network architectures implement targeted functions according to the characteristics of the signals. Convolutional Neural Networks (CNNs) excel at extracting facial image features; for example, certain CNN models use multiple convolutional sub-networks to perform face detection and keypoint localization, providing precise coordinates for subsequent calculation of eye and mouth aspect ratios [3]. Recurrent Neural Networks (RNNs) and their variants focus on temporal feature processing. Their included Long Short-Term Memory (LSTM) networks can effectively capture the temporal dependencies of physiological signals. Using LSTM-based models to analyze EEG data can improve the accuracy of pilot cognitive load recognition. Moreover, multimodal fusion recurrent neural networks (MFRNNs) extract temporal information from heart rate, eye, and mouth features through multiple sub-networks and then fuse these features via a relational layer, achieving high fatigue recognition accuracy and demonstrating greater robustness under lighting interference compared to traditional models. Attention mechanism fusion models further optimize the utilization of multimodal features. Some models incorporate multi-head cross-attention and segmented wavelet attention, fusing EEG, peripheral physiological signals, and facial features; the emotion recognition accuracy on specific datasets reaches 86.75%, providing effective reference for multimodal data fusion in SPO scenarios [3].

In addition, a proposed CNN-LSTM hybrid model extracts spatial features of physiological signals using CNN and captures temporal dependencies with LSTM, achieving an accuracy of 86.38% in multimodal driving state monitoring. Its architectural design offers insights for optimizing deep learning models in SPO scenarios [5]. Related reviews mention Transformer-based models, which perform well in managing long temporal correlations in facial videos and physiological signals, offering new model options for long-duration flight state monitoring under SPO [7].

5. Research Status and Challenges

Current research has validated the effectiveness of driving state monitoring technology under the SPO model. Facial features (such as the percentage of eyelid closure and eye aspect ratio) and physiological signals (such as heart rate variability and EEG signals) can well characterize driving states, and related technical solutions provide strong support for this [2, 9]. The accuracy of evaluation models has also been significantly improved. Deep learning models like MFRNN and NMSNet, leveraging multimodal fusion and temporal feature capture capabilities, have increased state recognition accuracy to over 94%, outperforming traditional machine learning models. At the same time, to address interference caused by cabin lighting and vibration, studies have optimized signal acquisition through technologies such as infrared imaging and wavelet denoising; for example, the anti-light interference capability of a certain RGB-D camera solution was improved by 30% [2].Moreover, actual road tests have verified the feasibility of collaborative monitoring of multiple physiological indicators. The differential LF/HF threshold division method proposed by related studies provides experimental evidence for quantifying pilot fatigue levels under the SPO model [6]. Other research points out the advantages of remote photoplethysmography (rPPG) in non-contact physiological signal acquisition, while also noting challenges such as head movement and lighting changes, which closely align with the current challenges faced by SPO monitoring technology [7].

The existing issues mainly include three aspects: First, the accuracy and stability of monitoring technology are insufficient. Facial features are easily obstructed by helmets or oxygen masks, leading to errors in key point positioning. Physiological signal acquisition devices such as EEG headsets are difficult to balance non-invasiveness and comfort, and long-term wearing can cause discomfort to pilots [8]. Second, there is a lack of data privacy and security. Sensitive physiological signals of pilots, such as EEG and HRV, lack encryption for transmission and storage, posing a risk of leakage. Third, the generalization and interpretability of models are poor. Models trained on ground-based datasets, when transferred to SPO scenarios, show a 10%-15% decrease in generalization accuracy due to high-altitude hypoxia and other task characteristics. Moreover, the 'black box' nature of deep learning models like MFRNN cannot explain decision-making, which does not meet the traceability requirements of the aviation industry. The challenges faced include the lack of unified standards and regulations. Under the SPO mode, thresholds for fatigue PERCLOS, data acquisition frequency, and model performance evaluation standards are not yet standardized, resulting in difficulties in comparing and promoting research outcomes.

6. Conclusion

This study systematically reviews research on driver state monitoring based on facial features and physiological signals under the single-pilot operation (SPO) mode. Starting from the basic characteristics of the SPO mode, it organizes the monitoring technology system for facial features and physiological signals, analyzes data fusion methods and the performance of machine learning and deep learning evaluation models, and finally summarizes the achievements, challenges, and future directions.

Theoretically, this study integrates the SPO driver state monitoring technology framework, clarifies the synergistic representation mechanism of facial features and physiological signals, and overcomes the limitations of single signals; practically, it extracts suitable technologies such as RGB-D cameras and non-invasive EEG devices, as well as models like MFRNN and NMSNet, providing pathways for the development of monitoring systems.

The study has limitations, including not covering SPO emergency scenario monitoring and insufficient analysis of signal features under high-stress conditions; it also lacks validation through real SPO cockpit experiments, leaving the engineering applicability of the results to be assessed.

In the future, it is necessary to strengthen interdisciplinary collaboration, conduct more empirical studies, and promote practical applications of the technology to advance the development and implementation of SPO driver state monitoring technologies.

References

[1] Wang M, Xiao G, Wang G Q. Single-pilot operation mode technology. Acta Aeronautica et Astronautica Sinica, 2020, 41(4): 323541.

[2] Du T, Li C, Li P X, Liu D, Li L. Vision-Based Fatigue Driving Recognition Method Integrating Heart Rate and Facial Features. IEEE Transactions on Intelligent Transportation Systems, 2021, 22(5): 3089-3100.

[3] Chen X H. Research on fatigue driving detection method based on driver's facial features and physiological signals. Master's Thesis, Jilin Institute of Chemical Technology, Jilin, China, 2023.

[4] Lu B. Research on driving fatigue detection based on multiple types of human physiological signal features. Master's Thesis, Northeast Electric Power University, Jilin, China, 2022.

[5] Zhou S, Zhang N, Duan Q, et al. Monitoring and Analyzing Driver Physiological States Based on Automotive Electronic Identification and Multimodal Biometric Recognition Methods. Algorithms, 2024, 17(12): 547.

[6] Chang Y L, Feng Y C, Chen O T C. Real-Time Physiological and Facial Monitoring for Safe Driving. In: Proceedings of IEEE International Conference on Systems, Man, and Cybernetics, Budapest, Hungary, 2016: 4849-4852.

[7] Xiang G, Ou Y, Li J, et al. Recovering Physiological Signals From Facial Videos: Recent Advances and Applications in Intelligent Vehicles. IEEE Transactions on Intelligent Vehicles, 2024, 9(10): 6576-6598.

[8] Szwoch W. Using Physiological Signals for Emotion Recognition. In: Proceedings of HSI 2013, Sopot, Poland, 2013: 556-561.

[9] Li J. Research on multimodal emotion recognition based on EEG, peripheral physiological signals and facial expressions. Master's Thesis, Nanjing University of Posts and Telecommunications, Nanjing, China, 2023.

[10] Yang J C, Wei F, Lin L, et al. Review on driver fatigue driving detection research. Journal of Shandong University (Engineering Science), 2024, 54(2): 1-12.