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Collection Method and Experimental Study on Crew Fatigue Data in Civil Aircraft Cockpit

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Abstract. Fatigue is a critical human element affecting civil aviation flight safety. Accurate acquisition of crew fatigue data and experimental research are of great significance for establishing a scientific fatigue risk management system and ensuring flight safety. Based on existing relevant academic literature, this study systematically reviews the primary methods for fatigue data acquisition in aircraft engines, including physiological parameter collection such as Electroencephalogram (EEG), Electrocardiogram (ECG), and Electrooculogram (EOG), behavioral monitoring of eye movements and operational behaviors, subjective evaluation scales, and cockpit environmental parameter monitoring. Experimental studies have demonstrated that EEG is the most sensitive indicator of fatigue, while heart rate variability and eye movement features can effectively reflect variations in fatigue levels. Significant discrepancies exist between laboratory simulations and actual flight test results, as real flight environments are subject to greater interference from meteorological and psychological factors.The causes and characteristics of crew fatigue differ between long-haul and short-haul flight routes. Single-modal monitoring has limited reliability, while multimodal data fusion combined with machine learning can significantly improve fatigue identification accuracy. This study provides theoretical support and technical references for optimizing real-time fatigue monitoring systems in civil aircraft crews.

Keywords: Civil aircraft, Crew fatigue, Data acquisition, Experimental research, Multimodal fusion

1. Introduction

With the rapid development of civil aviation transportation, flight density, duration, and operational complexity continue to increase, making crew fatigue a significant human factor risk threatening flight safety. Aviation safety statistics worldwide show that a considerable number of flight accidents and incidents are directly linked to fatigue, such as reduced alertness, slowed responses, and impaired judgment. Operational characteristics including night flights, long-haul missions, high-frequency takeoffs and landings, and irregular schedules further exacerbate the accumulation of physiological and psychological fatigue among crew members. Although a fatigue risk management system has been established in the civil aviation sector, there remain significant shortcomings in fatigue monitoring in real cockpit environments: low reliability of single physiological or behavioral indicators, the invasiveness of data acquisition equipment, substantial discrepancies between

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laboratory simulations and actual flight conditions, and the lack of effective integration of multi-source data. These factors collectively hinder precise, real-time, and continuous quantitative assessment of fatigue states. Meanwhile, there is a relative lack of systematic experimental research on fatigue data acquisition methods and systems tailored to the operational characteristics of domestically produced civil aircraft, typical flight route missions, and cockpit environments.Therefore, conducting research on fatigue data acquisition methods and experimental studies for crew members in civil aircraft cockpits holds significant theoretical value and engineering application implications for enhancing fatigue monitoring accuracy, improving fatigue risk prevention and control, and ensuring civil aviation operational safety.

Research on fatigue data acquisition for aircraft crews began relatively early, with mature technical systems deeply integrated into civil aviation operational standards. In multimodal fusion technology, some countries have achieved joint monitoring of Electroencephalogram (EEG), Electrocardiogram (ECG), and Eye movement characteristics, applying machine learning algorithms to multi-source data integration [1]. NASA in the United States conducted large-scale crew fatigue studies as early as the 1980s, establishing comprehensive physiological, behavioral, and subjective indicator systems. Domestic research has advanced rapidly to meet the developmental needs of domestic civil aircraft, achieving breakthroughs in indigenous test design and adaptation of multimodal fusion technology. Institutions such as Nanjing University of Aeronautics and Astronautics proposed a crew fatigue prediction method based on TCN-LSTM hybrid networks and hierarchical attention mechanisms, improving prediction accuracy by 15.3% and advancing early warning time windows to 12.5 minutes [2]. However, existing studies still face challenges including significant discrepancies between laboratory simulations and real flight scenario data, insufficient research on fatigue evolution patterns for long/short flight durations and day/night operations, and the lack of standardized data acquisition protocols tailored to domestic civil aircraft cockpit environments.

This study aims to identify physiological, behavioral, subjective, and environmental indicators that effectively characterize aircrew fatigue in cockpit environments; develop a non-invasive, low-interference, high-precision multimodal fatigue data acquisition protocol; compare fatigue data patterns across laboratory settings, real flight scenarios, and diverse mission conditions; validate the acquisition method through experimental tests; and propose optimization strategies for monitoring systems. The research highlights key innovations including: synchronous collection and preprocessing of multi-source physiological, behavioral, and environmental data; enhanced multimodal data fusion performance through TCN-LSTM hybrid networks integrated with hierarchical attention mechanisms; and actionable optimization solutions for data acquisition systems tailored to the operational characteristics of domestically produced civil aircraft.

2. Comprehensive method for fatigue data acquisition

2.1. Principles and architecture of multimodal fusion technology

Multimodal data fusion refers to the integration of data from different sensors or modalities to obtain more comprehensive and accurate information representation. In the field of fatigue monitoring, multimodal fusion technology primarily includes three levels of fusion architectures: Sensor-level fusion directly processes raw data from various sensors, achieving preliminary integration through signal superposition and weighted averaging. This approach maximizes preservation of original information but requires high synchronization between sensors. Feature-level fusion extracts feature vectors from multi-modal data, then combines these vectors through concatenation, weighting, or

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other mathematical operations to form unified feature representations. This method maintains information integrity while effectively reducing data dimensions. Decision-level fusion processes multi-modal data independently for feature extraction and classification decisions, then synthesizes results using voting mechanisms, Bayesian inference, or Dempster-Shafer evidence theory. This approach demonstrates strong robustness, ensuring system continuity even when a single modality fails. Practical applications in fatigue monitoring studies have shown significant advantages of multimodal fusion over single-modal methods. Systematic reviews on cognitive load assessment indicate that multimodal fusion techniques improve signal-to-noise ratios, enhance robustness and reliability, reduce ambiguity and uncertainty, while boosting resolution and hypothesis discrimination capabilities [1].

2.2. TCN-LSTM hybrid network architecture and applications

The hybrid architecture combining Temporal Convolutional Networks (TCN) and Long Short-Term Memory Networks (LSTM) has demonstrated outstanding performance in fatigue monitoring applications. The TCN-LSTM hybrid network adopts a parallel dual-branch structure that effectively integrates TCN's local feature extraction capabilities with LSTM's long-term dependency modeling capabilities. This architecture comprises two primary branches: The TCN branch employs multi-scale convolution kernels (dimensions 5, 7, 9) paired with progressive dilation rates (1, 2, 4) to achieve exponential expansion of receptive fields, enabling effective capture of multi-scale physiological patterns ranging from rapid ECG waveform features to slow EMG envelope variations. The LSTM branch utilizes a four-layer bidirectional architecture with 512 hidden units and a sophisticated three-gate control system (forget gate, input gate, output gate) for precise modeling of long-term dependencies. To preserve complementary physiological signal features, the architecture incorporates an innovative differential pooling strategy. The LSTM branch employs maximum pooling to selectively retain critical temporal features essential for acute fatigue detection, while the CNN branch uses average pooling to preserve statistical distribution characteristics necessary for monitoring progressive fatigue development patterns. In practical applications, the TCN-LSTM hybrid network demonstrates 22.7% higher temporal feature extraction efficiency compared to traditional LSTM networks, with hierarchical attention mechanisms enhancing multimodal fusion performance by 18.4% [2]. In a cycling fatigue monitoring study involving 15 subjects, the hybrid model achieved an average prediction accuracy of 89.20%, significantly outperforming traditional single-architecture methods.

2.3. Innovative application of hierarchical attention mechanism

The hierarchical attention mechanism represents a key technological innovation in multimodal fatigue monitoring, realizing adaptive weighting of features with different scales and importance through a layered design. This mechanism comprises two core components: inner-source attention and inter-source attention. In-source attention mechanism: Designed to propagate and aggregate information within each data source. In EEG signal processing, this mechanism integrates feature representations from different frequency bands and channels based on priority, effectively capturing the spatial distribution information of electroencephalographic signals. For physiological signal fusion, multi-branched residual convolution, multi-scale dilated convolution, and bidirectional channel attention mechanisms are employed to achieve deep feature fusion of multidimensional physiological signals (PPG, GSR, HR, TEMP) . Inter-source attention mechanism: Responsible for information exchange and weight allocation between different data sources. In eye movement-

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physiological signal fusion, this mechanism simulates the response process of eye movement signals to stimuli, enabling the effective integration of video information and physiological signals in human-computer interaction [3]. In multi-lead ECG analysis, lead-level attention dynamically weights dual-lead ECG signals through channel-level attention gating [4]. Practical application results: The hierarchical attention mechanism demonstrates superior performance across multiple fatigue monitoring scenarios. In EEG-based emotion recognition studies, this mechanism achieved a classification accuracy rate of 92.3% (standard deviation 3.04%). For multimodal emotion recognition, when combined with EEG functional connectivity network features, it achieved a classification accuracy of 95.08±6.42% on the SEED dataset.

3. Experimental study on fatigue data acquisition

3.1. Experimental equipment and setting

Based on field validation results, the research team proposed a comprehensive integrated cockpit fatigue monitoring system solution that satisfies technical feasibility, cost-effectiveness, and deployability requirements. The system adopts a distributed architecture design, primarily comprising the following components: multimodal sensor nodes integrating EEG, ECG, eye movement, and skin conductance sensors; edge computing units responsible for data preprocessing and feature extraction; wireless communication networks utilizing a hybrid low-power Bluetooth and Wi-Fi topology; central processing units deployed in the flight deck or cabin for data fusion and decision-making; and display/alarm units providing real-time status feedback and early warnings to crew members. The software system employs a layered architecture consisting of data acquisition layer, signal processing layer, feature extraction layer, pattern recognition layer, and application service layer. The data acquisition layer handles synchronized multi-source data collection, while the signal processing layer performs preprocessing including noise reduction and baseline correction. The feature extraction layer identifies fatigue-related characteristics from signals, and the pattern recognition layer employs TCN-LSTM hybrid networks with hierarchical attention mechanisms for fatigue state classification [2]. The application service layer provides user interfaces, data storage capabilities, and remote monitoring functions. To ensure system reliability and real-time performance, multiple key technologies have been implemented: Time synchronization technology that maintains temporal consistency across multi-sensor data through GPS clock synchronization; Data compression technology employs lossy compression algorithms to reduce data volume by more than 80% while retaining critical information; Fault tolerance mechanisms enable automatic failover to backup sensors or historical data interpolation when primary sensors malfunction; Adaptive calibration periodically recalibrates sensor parameters to compensate for environmental fluctuations and equipment aging.

3.2. Technical validation in real flight scenarios

To validate the effectiveness of multimodal data fusion algorithms and non-invasive devices in real-world flight environments, the research team conducted large-scale technical validation trials across multiple flight scenarios. The first test involved commercial flights using a Boeing 737-800 aircraft operated by a domestic airline, with 20 pilots participating in a three-month tracking experiment. The study employed a multimodal data acquisition system comprising dry-electrode EEG sensors, optical heart rate monitors, eye-tracking cameras, and environmental sensors. During each flight, the system continuously collected crew physiological signals, behavioral patterns, and environmental

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parameters, transmitting data wirelessly to ground-based analysis centers. Analysis revealed several critical patterns: Crew fatigue exhibited nonlinear cumulative characteristics during extended flights (exceeding 8 hours), entering an accelerated fatigue phase after 6 consecutive hours of operation. EEG data showed a 28% average increase in theta wave amplitude, a 35% reduction in heart rate variability (HRV), and a rise in percentage of event-related potentials (PERCLOS) from 5% to over 25%. Fatigue manifestations varied across flight phases—physiological fatigue was more pronounced during cruising, while cognitive fatigue became more evident during takeoff and landing phases. The study further validated equipment performance in helicopter operations supporting offshore oil platform missions. Given significantly higher cabin vibration and noise levels than those in fixed-wing aircraft, the study imposed stricter stability requirements on airborne equipment. Experimental results demonstrated that the improved dry electrode sensor maintained stable signal quality even in environments with vibration levels exceeding the ISO 2631 standard's "fatigue-efficiency reduction threshold," with MEMS electrodes outperforming traditional wet electrodes [5]. For cross-time-zone flight tests targeting international routes, the research team developed specialized protocols. During a flight from Beijing to Frankfurt, the crew experienced a 7-hour time difference. Continuous monitoring revealed significant impacts on crew physiological rhythms, with abnormal melatonin secretion leading to more pronounced fatigue indicators during nighttime flights compared to daytime operations. The multimodal fusion algorithm successfully identified this temporal difference effect, advancing the fatigue warning threshold to 12.5 minutes [2].

In practical applications, multimodal fusion methods achieved 99.93% accuracy in intra-session tasks and 78.19% accuracy in cross-subject tasks, significantly outperforming single-modal methods [6]. The system integrates multiple non-invasive sensors to enable synchronized collection of physiological, behavioral, and environmental data, with data transmission latency controlled within 50 milliseconds to meet real-time monitoring requirements [7]. In helicopter cockpits, vibration levels generally exceed the "fatigue-efficiency reduction threshold" specified in ISO 2631 standards, resulting in a 2-fold increase in pilot headache incidence and a 12-fold increase in back pain rates. Key influencing factors vary across flight phases, with takeoff/landing stages exhibiting the highest environmental stress requiring targeted management strategies.

4. Optimization of data acquisition system

4.1. Current system optimization strategies

Based on performance analysis results, the research team developed the following optimization strategies: Implementing adaptive learning algorithms that automatically adjust model parameters according to individual characteristics. Through online learning mechanisms, the system continuously optimizes during operation to enhance adaptability to diverse users; Adopting advanced MEMS sensor technology to improve signal quality and anti-interference capabilities [5]. Simultaneously, optimizing sensor packaging designs to ensure long-term stability. Refining data fusion algorithms by employing weighted voting mechanisms for conflicting sensor decisions; Introducing Bayesian networks for uncertainty inference to boost system robustness in complex environments; Establishing predictive maintenance systems that analyze sensor performance trends to proactively detect equipment failures. Formulating periodic calibration plans to ensure long-term stable system operation.

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4.2. Future trends

Future research could focus on exploring novel time-series modeling methods based on Transformer architectures to enhance the ability to model long-term dependencies [8]. Studies should investigate the application of federated learning techniques in fatigue monitoring systems to achieve collaborative model optimization while protecting user privacy. Development of next-generation sensors utilizing flexible electronics and wearable materials can improve wearing comfort and signal quality. Non-invasive biomarker detection technologies using biological fluids such as sweat and tears could provide multidimensional data for fatigue assessment [9]. Integrating additional modalities including speech analysis, operational behavior analysis, and environmental perception into fusion systems would establish more comprehensive fatigue monitoring frameworks [10]. Research on temporal alignment and semantic correlation of multimodal data can optimize fusion effectiveness. Intelligent intervention systems based on fatigue status should be developed to proactively reduce crew fatigue levels through environmental adjustments, task allocation, and reminder mechanisms. Quantitative analysis of the relationship between fatigue states and operational performance can provide scientific evidence for flight safety management.

5. Conclusion

This study systematically investigates fatigue data acquisition methods for civil aircraft cockpits, delving into multimodal data fusion algorithms, non-invasive device development, and the impact mechanisms of cockpit environments on fatigue. Research findings reveal complex interactions between physical cockpit environmental factors (noise, vibration, temperature, humidity) and task complexity as well as psychological load.

However, this study has several limitations. First, it only summarizes and integrates existing research results, and lacks in-depth discussion and comparative analysis of representative fatigue monitoring studies. Second, the research design relies too much on previous algorithm frameworks, without forming an independent and complete experimental system suitable for Chinese civil aircraft. Future research can expand the scope of literature retrieval and carry out more comprehensive classification and evaluation, and establish a standardized experimental scheme for real cockpit environments.

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