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Research on Fatigue Data Collection Methods for Civil Aviation Cockpit Crews

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Abstract:

The single pilot operation (SPO) mode has become a promising solution to address the critical lack of qualified pilots and rising costs in the civil aviation industry. However, this operational mode introduces challenges in pilot fatigue management, as the single pilot must afford the entire operational workload without the replacement and cross-monitoring traditionally provided by a co-pilot. Therefore, pilots' fatigue detection and management are becoming important. This paper systematically reviews current methodologies for pilot fatigue data collection, providing a comparative analysis of physiological signal monitoring techniques, including electroencephalogram, electrocardiogram, and electrooculogram, and non-contact image-based behavioral analysis technologies. This paper proposes a multimodal fusion framework that combines data from wearable physiological sensors with computer vision-based behavioral monitoring. Comprehensive system architecture encompasses four dedicated layers: multimodal data acquisition, advanced signal processing, intelligent feature fusion, and dynamic alerting. By leveraging machine learning algorithms, the system enables real-time, accurate fatigue assessment with enhanced robustness. This multimodal strategy effectively mitigates the constraints of single-method systems, providing a reliable and scalable technological foundation for ensuring aviation safety in the evolving SPO environment.

Keywords: Fatigue Detection; Single-Pilot Operations; Physiological Signals; Image-Detection

1. Introduction

With the advancement of aviation technology and increasing economic pressures, Single-Pilot Operations (SPO) has emerged as a critical future operational model under active exploration within the civil aviation industry [1]. SPO refers to an operational paradigm where a single pilot accomplishes flight missions assisted by advanced automation systems. Specifically, during flight operations, except for critical procedures requiring dedicated „Single-Pilot Operations," the aircraft can be controlled by one pilot during relatively low-risk phases such as cruise. In contrast, during high-risk phases like takeoff and approach, the operational aircraft is managed through collaboration between one pilot in the cockpit and a remote ground operator. This represents a fundamental departure from the currently prevalent multi-crew collaborative model. The International Civil Aviation Organization (ICAO), the European Union Aviation Safety Agency (EASA), and major aircraft manufacturers are actively promoting research and application of SPO-related technologies, with commercial aviation SPO implementation anticipated within the next 10-15 years [2].

In the SPO environment, pilot fatigue becomes particularly prominent and critical. Compared to traditional multi-crew models, SPO lacks the collaborative monitoring and alternating rest opportunities provided by a co-pilot, requiring the single pilot to independently assume all operational responsibilities and decision-making pressures. According to research reports from EASA, pilot workload in SPO increases by over 30%, with fatigue accumulation accelerating markedly during long-haul flights and abnormal situation management [2]. This establishes fatigue monitoring and management as a core technical challenge for ensuring SPO operational safety.

According to the EASA definition, fatigue constitutes an impaired state caused by sleep loss, prolonged wakefulness, or excessive workload. This compromised condition leads to diminished cognitive capacity and elevated error rates. Consequently, developing effective detection methods and implementing measures to mitigate pilot fatigue have become crucial imperatives for maintaining aviation safety within the SPO framework [3].

2. Current Research Status

The SPO operational model offers potential benefits including reduced airline operating costs, alleviation of pilot shortages, and enhanced aircraft utilization. However, it simultaneously introduces significant challenges regarding increased pilot fatigue levels. In traditional dual-pilot cockpit operations, two pilots can alternate tasks, cross-verify monitoring functions, and rotate rest periods, thereby partially mitigating fatigue‘s impact on flight safety. Under the SPO paradigm, however, a single pilot must operate independently during critical phases without assistance or supervision from another pilot. Should this pilot experience fatigue, the consequences could be catastrophic [4].

2.1 Particularities of Fatigue Research in the SPO Mode

The SPO model introduces a qualitative change in pilot workload. In traditional crew configurations, operational tasks can be distributed between the captain and co-pilot, providing natural opportunities for rest and recovery. In contrast, SPO requires the single pilot to maintain continuous high alertness and assume operational, monitoring, and decision-making responsibilities across all flight phases. This shift in workload characteristics directly influences both the rate at which fatigue accumulates and its manifestations. Fatigue in SPO pilots often presents as cognitive resource depletion rather than mere physiological drowsiness, thereby generating new requirements for data collection methodologies—greater emphasis must be placed on monitoring higher-order cognitive functions, extending beyond basic physiological metrics [5].

In conventional flight operations, the co-pilot not only shares the workload but also fulfills critical functions of mutual monitoring and intervention. When the captain exhibits signs of fatigue, the co-pilot can provide timely alerts or even assume control of operations. In the SPO environment, this human safety net is entirely absent, compelling the pilot to rely exclusively on automated systems for monitoring and alerts. This paradigm shift places extremely high demands on the reliability of fatigue data acquisition systems. Such systems must be capable of real-time, accurate fatigue state identification and deliver effective intervention measures at appropriate times. Any instance of false alarms or missed detections could lead to severe consequences, fundamentally distinguishing this context from traditional operational environments with multi-crew backups [6].

Table 1 shows comparison of fatigue risk between spo and traditional unit patterns.

Table 1. Comparison of Fatigue Risk Between SPO and Traditional Unit Patterns

Feature Dimension	Traditional Crew Pattern	SPO Pattern	
Workload Distribution		Single-person independent operation	

Monitoring Mechanism	Mutual personnel monitoring	Reliance on monitoring systems	Reduction in safety
Rest Opportunities			Fewer recovery opportunities
Emergency Support	Immediate personnel support		Increased response delay
Skill Maintenance		Highly automated operation	

2.2 Fatigue Detection Methods

Fatigue detection methodologies are primarily categorized into two groups: physiological signal monitoring and behavioral observation-based monitoring. Physiological signal detection methods employ sensors to capture signals such as electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), respiratory signals, and galvanic skin response (GSR), with fatigue levels assessed based on these physiological indicators [7]. Behavioral monitoring methods utilize cameras or sensors to capture behavioral characteristics like eye closure, head posture, yawning frequency, and movement retardation to determine pilot fatigue [8].

Given the individual variability in fatigue manifestation and its diverse symptoms, reliance on a single detection method often proves insufficient for completely accurate assessment, as each unimodal approach possesses inherent limitations. Consequently, detection systems incorporating multi-modal information fusion currently represent one of the more promising solutions for the SPO environment [9]. This paper primarily discusses existing fatigue sensing technologies within the cockpit environment, compares the advantages and disadvantages of various physiological signal detection methods, proposes potential improvements, and ultimately establishes a simulation test platform to validate the feasibility and effectiveness of a multi-modal fatigue detection system in a single-pilot cockpit scenario [10].

2.3 Physiological Signal Detection Methods Based on Wearable Devices

In single-pilot operations, the absence of alternating pilots and human safety redundancy makes fatigue detection critically important. As physiological signals constitute the most direct and readily observable indicators of human fatigue, detection methods leveraging these signals are both direct and effective [1]. Various sensor technologies can acquire human physiological parameters such as EEG changes, heart rate variability (HRV), and eye movements. By analyzing large datasets, reliable models can be developed for real-time detection and judgment of pilot fatigue states during flight [2].

2.3.1 Fatigue detection based on electroencephalogram (EEG) signals

EEG-based fatigue detection typically involves several steps: electrodes placed on the scalp record EEG signals, which represent subtle electrical activities of the brain; the acquired signals undergo preliminary preprocessing to remove irrelevant information, commonly employing methods like wavelet transform for frequency band division (δ, θ, α, β) or Fourier transform to generate time-frequency spectrograms [3].

Subsequently, relevant and significant features are extracted from the processed EEG signals. These may include statistical data such as mean, variance, or entropy, features like texture, or directly obtained time-frequency features [4]. The objective is to distinguish characteristic patterns associated with alertness or fatigue based on these features.

Finally, the selected features are fed into machine learning or deep learning models to determine whether the driver is in an alert or fatigued state. Traditional models may include Support Vector Machines (SVM) or k-Nearest Neighbors (k-NN), while more advanced approaches might utilize Convolutional Neural Networks (CNNs) to learn spatial patterns or Recurrent Neural Networks (RNNs) to capture temporal dynamics, thereby classifying the driver‘s state as alert or fatigued [5].

2.3.2 Fatigue detection based on electrocardiogram (ECG) signals

Electrocardiogram (ECG) records the electrical depolarization process of the heart using surface electrodes. Fatigue can lead to reduced Heart Rate Variability (HRV), with decreased HRV and changes in the Low Frequency/High Frequency (LF/HF) ratio indicating autonomic nervous system imbalance [6]. ECG-based fatigue detection primarily relies on HRV analysis, extracting features from ECG/NN intervals in the time domain (e.g., SDNN), frequency domain (e.g., LF/HF ratio), and non-linear domains (e.g., Poincaré plots, entropy, multifractal analysis), along with heart rate fragmentation features [7]. After feature selection using methods like mutual information, classifiers such as ensemble learning (Random Forest, AdaBoost) or SVM are employed to build decision models [8]. Under ideal controlled datasets and with robust feature engineering, cross-validation results can approach 98% accuracy. However, challenges such as motion artifacts, labeling noise, and inter-sensor variability significantly impact system performance when deployed in wearable or real-world driving scenarios [9]. Therefore, ensuring real-time reliability necessitates signal quality control, accelerometer-assisted artifact rejection, and individualized calibration to enhance system robustness [10].

2.3.3 Fatigue detection based on electrooculogram (EOG) signals

Electrooculogram (EOG) is an effective physiological method for fatigue detection, measuring the corneo-retinal potential difference to capture eye movements, blinks, and eyelid behavior [11]. In practice, electrodes placed near the eyes record horizontal and vertical eye movements, collecting raw signals during sustained operation. These signals are often contaminated by noise from facial muscle activity and head movements, requiring preprocessing steps like band-pass filtering and wavelet decomposition to remove artifacts while preserving meaningful ocular information [12]. Various features can be extracted from the preprocessed EOG data, including blink duration, saccadic velocity, sample entropy, variance, and energy, which strongly correlate with drowsiness and reduced alertness [13]. Statistical methods like Analysis of Variance (ANOVA) select the most significant features, while dimensionality reduction techniques like Principal Component Analysis (PCA) help optimize the feature set [14]. These features are then input into machine learning classifiers such as Support Vector Machine (SVM), k-Nearest Neighbors (KNN), or ensemble models to differentiate driver states like normal, fatigued, drowsy, visually inattentive, and cognitively inattentive [15]. Thus, EOG offers a non-invasive yet accurate fatigue monitoring method, achieving detection accuracy exceeding 90% when combined with appropriate signal processing and classification techniques [16].

2.3.4 Fatigue detection based on electromyogram (emg) signals

Electromyogram (EMG) utilizes surface or intramuscular electrodes to detect electrical activity in muscles. During fatigue testing, facial or neck muscles are often monitored, as fatigue leads to reduced muscle strength and decreased EMG amplitude [17]. Unlike EEG and ECG, EMG primarily monitors peripheral rather than central fatigue. Recent studies have integrated EMG signals into multi-modal fatigue detection systems [18]. However, challenges such as ensuring precise sensor placement and artifacts from subject movement can lead to errors in practical applications of these systems [9].

2.3.5 Fatigue detection based on other physiological signals

Other physiological signals can also characterize fatigue levels. For instance, respiratory monitoring signals, acquired using chest bands or non-contact radar sensors, capture respiratory rate and respiratory rate variability, which tend to increase with drowsiness. Similarly, Galvanic Skin Response (GSR) signals measure increased skin conductivity due to elevated sympathetic nervous system activity, indicating decreased arousal levels in fatigued states. Furthermore, some of these signals, being relatively low-intensity and unobtrusive, are suitable for integration into wearable devices, though they are susceptible to environmental noise and significant inter-individual variability.

Different physiological modalities offer distinct advantages and disadvantages in fatigue detection: EEG detects cognitive fatigue, ECG reflects autonomic nervous system stress, EOG indicates visual fatigue, EMG reveals muscle fatigue, respiration reflects overall arousal state, and GSR indicates sympathetic nervous system overexcitation. While single-modality approaches provide substantial information, they are often plagued by high noise, significant inter-individual variability, and practical inconveniences, limiting accurate fatigue assessment. With advancements in multi-signal joint detection and machine learning algorithms, their application is expected to expand.

2.4 Image-Based Non-Contact Fatigue Detection Methods

In the Single-Pilot Operations (SPO) environment, non-contact fatigue detection methods, being less intrusive as they require no wearable sensors, have attracted significant research attention. Image-based detection methods primarily use cameras to capture pilots‘ facial expressions and behavioral characteristics, employing computer vision and machine learning algorithms for fatigue state recognition.

2.4.1 Key technologies in image detection*

The process begins with face detection and localization, utilizing features like Haar, HOG, or real-time models such as YOLO and MTCNN to identify and track the driver‘s facial region for subsequent fatigue analysis. This is followed by eye feature analysis, where systems like PERCLOS (Percentage of Eyelid Closure over the Pupil) assess fatigue levels based on blink frequency, eye closure duration, and related metrics. Head pose analysis estimates the pilot‘s head tilt and nodding frequency via 3D modeling during flight, comparing these against baseline behaviors to identify states of micro-sleep or decreased attention. Simultaneously, detection processes monitor changes in facial expressions (e.g., yawning frequency, drooping corners of the mouth) as supplementary indicators. Furthermore, comprehensive fatigue assessment can incorporate behavioral patterns such as body movements and operational response delays.

2.4.2 Advantages and limitations of image detection methods

Table 2 shows comparative analysis of image-based and physiological detection methods. The advantages of image detection methods include: non-contact and non-interference, ease of integration into existing cockpit systems, compatibility with multi-modal information (e.g., infrared imaging), and suitability for long-term monitoring.

Their limitations are, firstly, susceptibility to significant influences from lighting conditions, obstructions, and posture changes; secondly, the need to address privacy concerns, coupled with high algorithmic complexity and challenges in real-time performance; concurrently, they impose high hardware requirements regarding camera resolution and frame rate.

Table 2. Comparative Analysis of Image-Based and Physiological Detection Methods

Detection Method	Contact Requirement	Accuracy	Real-Time Performance	Comfort Level	Applicable Scenarios
Physiological Signals (e.g., EEG/ECG)	Contact	High	Medium-High	Relatively Low	Laboratory settings, high-precision scenarios
Image Detection	Non-Contact	Medium-High	High	High	Actual cockpit environments, long-term monitoring
Multi-Modal Fusion	Partial Contact	Very High	Medium	Medium-High	Recommended solution for future SPO systems

3. Proposed Framework for an Integrated Fatigue Detection System

To enhance the accuracy of fatigue detection in the single-pilot cockpit environment, it is recommended to adopt a multi-modal fusion strategy. This approach integrates physiological signals with image-based behavioral data to construct a real-time, reliable, and pilot-friendly fatigue monitoring system.

3.1 System Architecture

To improve fatigue detection accuracy in the single-pilot cockpit environment, we propose designing an integrated fatigue monitoring system based on a multi-modal fusion strategy. This system would amalgamate physiological signals and image-based behavioral data, characterized by real-time operation, reliability, and user-friendliness. The system architecture is structured into four layers:

Data Acquisition Layer: Physiological signals are captured via wearable devices (e.g., EEG, ECG, and EOG sensors) integrated into helmets or garments. Simultaneously, infrared and visible-light cameras capture facial and behavioral images. Environmental sensors monitor factors such as illumination, temperature, and noise for data correction purposes.

Data Processing and Feature Extraction Layer: Features are extracted separately from the physiological signals (e.g., HRV, EEG band power, blink frequency) and the image signals (e.g., PERCLOS, head pose, yawning frequency). A sliding window technique is employed to facilitate real-time feature extraction and caching.

Fusion and Decision Layer: Machine learning models (e.g., SVM, Random Forest, LSTM, or Transformer) are applied to fuse the multi-source features. An attention mechanism can be introduced to dynamically weight the importance of different signal sources. This layer ultimately outputs a fatigue level (e.g., alert, mild fatigue, severe fatigue) and computes a corresponding confidence score.

Alert and Feedback Layer:*Upon detection of moderate or higher fatigue levels, the system triggers audiovisual alarms or haptic feedback (e.g., seat vibration). It can also automatically suggest rest breaks or initiate assisted flight modes, such as autopilot takeover.

3.2 System Advantages

The advantages of this system include:
1. Enhanced redundancy and robustness through complementary multi-source data, avoiding single points of failure.
2. Incorporation of online learning capabilities to adapt to individual pilot physiological and behavioral characteristics, thereby increasing adaptability.
3. Protection of pilot privacy through local processing of image data.
4. Inherent scalability, facilitating the future integration of additional sensors or algorithmic modules.

4. Summary

This system design effectively combines the high accuracy of wearable physiological signal detection with the high comfort of non-contact image-based detection, creating complementary strengths. Physiological signals (e.g., EEG, ECG, EOG) capture fatigue states directly at the central and autonomic nervous system levels, while image-based methods provide an intuitive and unobtrusive monitoring pathway through metrics like PERCLOS, head pose, and facial expressions. The multi-modal fusion mechanism further enhances the overall reliability of the system, making it particularly suitable for application scenarios in the SPO environment that demand extremely high safety and real-time performance. In the future, this system could be integrated with additional contextual data (e.g., mission phase and environmental information) to enable even smarter and more personalized fatigue monitoring and intervention.

Authors Contribution
All the authors contributed equally and their names were listed in alphabetical order.

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