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Research on Measuring Pilot Fatigue Data through Multimodal Data Fusion Based on SPO Mode

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Abstract:

Pilot fatigue detection is critical for aviation safety, as fatigue impairs pilots' cognitive functions, reaction speeds, and decision-making abilities, posing severe threats to flights and potentially leading to heavy property damage or even casualties. This paper focuses on pilots under the single-pilot operation (SPO) mode—where individual pilots take on all flight tasks (from navigation to system monitoring), bearing greater physical and mental workload and facing higher fatigue risks than in traditional multi-pilot settings—and adopts a fatigue decision analysis method based on multimodal data fusion. It comprehensively collects four key types of data: electroencephalogram (EEG) signals reflecting real-time brain activity, electrocardiogram (ECG) signals related to autonomic nervous system changes, electromyogram (EMG) signals capturing muscle tension (e.g., around the eyes and jaw), and partial facial features (like eyelid closure duration or blink frequency) that visually indicate fatigue. By integrating and analyzing these multi-dimensional data, the paper reviews the latest research progress in pilot fatigue detection, identifies shortcomings of existing methods (such as single-modal approaches being easily disturbed by environmental factors), and explores future research directions, aiming to provide targeted technical support for ensuring SPO-mode flight safety.

Keywords: Fatigue analysis; Physiological signals; Multimodal data; Facial features

1. Introduction

The operation of flight missions is generally a highly complex process, where pilots play a crucial role. Since pilots must maintain a high level of concentration throughout the flight, their average workload is greater, making them more prone to fatigue, which poses potential risks to flight safety. Therefore, real-time monitoring of pilot fatigue levels to ensure they do not enter a fatigued state during flights has

become a critical task for airlines. With continuous advancements in aerospace technology, the emergence of the single-pilot operation mode has introduced a new approach to flight operations. On one hand, it helps airlines reduce costs and improve efficiency; on the other hand, it further raises the requirements for pilot safety. To ensure flight safety, researchers have been exploring new methods for pilot fatigue detection, including physiological data analysis, behavioral feature analysis, and data fusion techniques. These methods can determine whether a pilot is fatigued based on bodily responses and provide corresponding alerts. Currently, self-reporting and questionnaires are still commonly used during flights to assess pilot fatigue levels. However, these methods are highly subjective, relying primarily on the pilot‘s own perceptions and judgments. Pilots may encounter various situations during flight that could lead to misjudgments of their fatigue state, resulting in detection errors. Traditional fatigue detection methods also include single physiological indicators such as electroencephalography (EEG) and heart rate. While these indicators can reflect pilot fatigue to some extent, fatigue is a complex physiological process, and single physiological data may fluctuate due to external factors. In China, research on fatigue detection has primarily focused on physiological indicators such as heart rate variability (HRV) and EEG signals. Internationally, significant progress has been made in this field. NASA in the United States has achieved world-leading advancements in high-precision EEG detection, while research institutions in Japan and Europe have made notable contributions in heart rate variability and galvanic skin response. Multi-dimensional data fusion can effectively compensate for the limitations of single-data assessments, enabling comprehensive and highly accurate detection of pilot fatigue states. This paper focuses on analyzing pilot fatigue in single-pilot operations through multi-modal fatigue data fusion, combining various physiological indicators such as facial features and behavioral characteristics to assess fatigue levels. Based on the scientific problem of pilot fatigue detection, this study categorically discusses pilot fatigue levels using different types of information (physiological signals, facial feature signals, driving behavior signals, and multi-modal data fusion). The main research contents are as follows:

On one hand, by measuring pilots‘ electroencephalogram (EEG) signals, electromyography (EMG) signals, and electrocardiogram (ECG) signals during simulated flights, and combining two scientific methods—K-Nearest Neighbors and Support Vector Machines—to comprehensively analyze the fatigue levels of pilots‘ brains and bodies during flight. On the other hand, by extracting facial features of pilots during simulated flights and analyzing a series of data from these features to assess pilots‘ fatigue levels. Finally, by integrating multi-angle physiological state information (such as ECG and EEG signals), the accuracy of fatigue level measurements under different modalities is comprehensively analyzed, thereby deriving the most effective measurement method.

2. Methods for Measuring Pilot Fatigue Levels

2.1 Manifestations of Pilot Fatigue Levels

Fatigue generally refers to a physiological phenomenon characterized by a decline in mental or physical function, which manifests in pilots as reduced alertness and the ability to perform safety-related operations. Common causes of pilot fatigue include sleep deprivation, circadian rhythm disruption, or workload. According to flight accident statistics from the U.S. Federal Aviation Administration (FAA), human factors are the primary cause of flight accidents. As shown in Fig.1, they account for over 73% of the total incidents, while only 12% of accidents are caused by the aircraft itself. [1-3]. Therefore, pilot operational errors are the primary cause of accidents, which also means that the fatigue state of pilots is crucial to flight safety. Fatigued piloting may lead to operational errors, thereby causing flight accidents [4].

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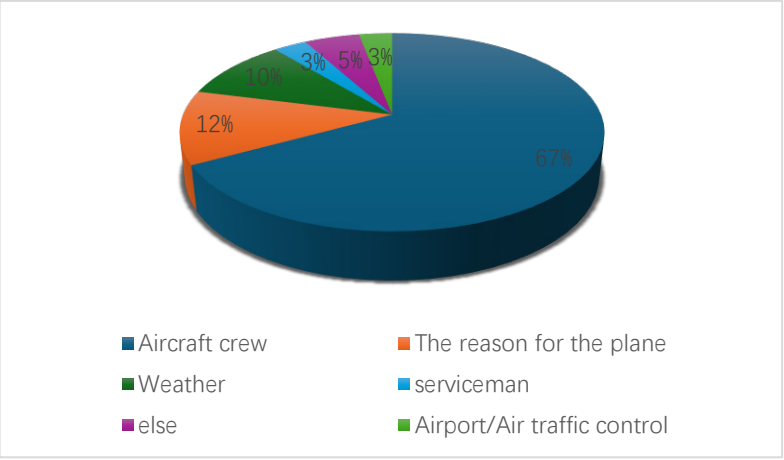

Fig.1 Global Civil Aviation Accident Analysis Chart [5]

2.2 Measurement Methods Based on Physiological Signal Characteristics

The detection methods based on physiological signal characteristics typically utilize electrocardiogram (ECG) signals (Electrocardiography, ECG) [6], electromyography (EMG) signals (Electromyography, EMG) [7], electrooculography (EOG) signals (Electrooculography, EOG) [8], electroencephalography (EEG) signals (Electroencephalography, EEG), etc., to assess the fatigue level of pilots. Compared to conventional subjective measurement methods, physiological signal measurements are more objective and accurate, better reflecting the pilot's operational state. They are particularly helpful in early detection and prevention of pilot fatigue, thus being widely applied.

2.2.1 Electrocardiogram (ECG) signals

ECG refers to the bioelectrical changes generated by the sequential excitation of the pacemaker, atria, and ventricles during heartbeats, which is a periodic signal with strong regularity. The changes in ECG signals are primarily assessed using the Heart Rate Variability (HRV) index. Currently, there are two popular methods for determining pilot fatigue levels through ECG signals: analyzing and classifying ECG signal data using the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) learning algorithms. A third-order Butterworth low-pass filter is employed to construct the ECG waveform diagram while preserving key features of the ECG signal, such as the P wave, QRS complex, and T wave, thereby enabling the extraction of HRV from the ECG signal. The KNN and SVM algorithms can then be used to analyze the fatigue level of the test subject [1].

Table 1. ECG Signal Waveband Information Table [1]

Waveband Name	Content
P wave	At this time, the atria are in an excited state
PR interval	The process of syncytial excitation being transmitted to the atrioventricular node
QRS complex	Syncytial excitation simultaneously stimulates the left and right ventricles, where the Q and S points are the low extreme points, and the R point is the high extreme point
ST segment	Ventricular myocardial cell depolarization ends, and repolarization has not yet begun
T segment	Ventricular repolarization

A complete heartbeat process consists of multiple different wave segments, each corresponding to a specific stage of cardiac electrical activity. As shown in Table 1, it mainly includes five stages and their corresponding components. Before extracting HRV from the ECG signal, it is necessary to determine the RR interval (the time interval between two consecutive R wave peaks). The variability of continuously measured RR intervals can be used to detect the heart's self-regulation ability and help assess the body's fatigue level. This paper mainly focuses on the time-domain extraction of HRV:

Mean RR interval (RR.Mean), the formula is:

$$RR.Mean=\frac{\sum_{i=1}^{R} RR_i}{R} \quad (1)$$

Where RR_i Represents the i-th RR interval.

Root mean square of successive RR interval differences (RMSSD), the formula is:

$$RMSSD=\sqrt{\frac{1}{N-1}\sum_{i=2}^{N}(RR_i-RR_{i-1})^2} \quad (2)$$

Where RR_i And RR_{i-1} Are adjacent RR intervals, respectively.

When using the K-nearest neighbors and support vector machine algorithms to analyze and classify ECG data, the seven-fold cross-validation and AUC metric validation methods showed that K-nearest neighbors has a stronger ability to correctly classify ECG fatigue states [1].

2.2.2 Electromyography (EMG) signal

EMG is an electrical signal that records muscle activity. Muscle fatigue causes changes in the amplitude, frequency, and timing characteristics of the EMG signal, mainly manifested as increased amplitude and decreased frequency [9]. The EMG signal indicates the muscle fatigue mechanism by analyzing the dynamic changes of the electrical signals generated by muscle activity over time and frequency. Through related research analysis, in the time domain, since more muscle fibers are recruited to compensate for fatigued muscle fibers, the signal amplitude usually increases, such as the root mean square value (RMS, reflecting signal energy and muscle activity level) and the integral of the absolute value of the signal (iEMG, reflecting the cumulative degree of muscle activity). During fatigue, RMS and iEMG typically increase [1].The relevant formulas for RMS and iEMG are as follows:

$$RMS=\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \quad (3)$$

$$iEMG=\int_{t_1}^{t_2}\left|x(t)\right|dt \quad (4)$$

Where x(t) is the instantaneous amplitude of the EMG signal, and t1 and t2 are the start and end times of the signal integration, respectively.

When using the K-nearest neighbors and support vector machine algorithms to classify and analyze EMG data, the seven-fold cross-validation and AUC metric validation methods were also employed. The results showed that the K-nearest neighbors algorithm outperforms the support vector machine in distinguishing between positive and negative categories [1].

2.2.3 Electroencephalography (EEG) signal

EEG is a measurement method characterized by high accuracy, high precision, and high real-time performance. EEG signals are at the microvolt level, making them highly susceptible to interference from external factors such as noise sources and artifacts, which not only reduce measurement accuracy but also pose significant challenges for data processing. Artifacts are divided into physiological artifacts and non-physiological artifacts (as shown in Fig. 2). Physiological artifacts arise from normal physiological activities of the individual and may not necessarily be related to EEG signals, but they can partially overlap with EEG signals, thereby affecting the measurement results. Non-physiological artifacts are typically caused by external operations and often do not align with the physiological state of the subject, thus impacting the measurement results [10].

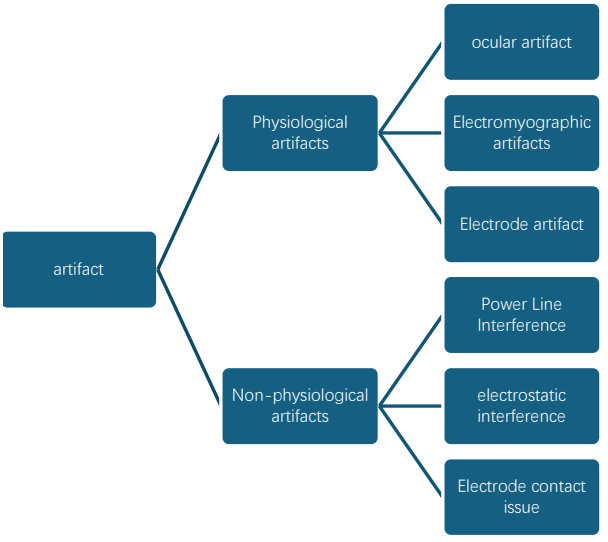

Fig. 2 Artifacts and their classification

During experiments, as long as the subject is in a conscious and open-eyed state, ocular artifacts are inevitably generated. These artifacts are caused by electrical signals from eye muscle movements, which interfere with EEG signal measurements. Therefore, measures must be taken to mitigate the impact of these electrical signals on the experimental objectives.

This paper employs a third-order Butterworth bandpass filter to minimize the interference of physiological and non-physiological artifacts on physiological signals [11]. Using frequency-domain analysis, EEG signals in the time domain are transformed into the frequency domain, and spectral estimation methods are applied for signal analysis while calculating averages to reduce errors [1].

When classifying and analyzing experimental data using the K-nearest neighbors (KNN) and support vector machine (SVM) methods, seven-fold cross-validation reveals that the classification accuracy of the KNN model is 64.99%, while that of the SVM model is 71.70%. This indicates that, in this experiment, the KNN method outperforms the SVM method in distinguishing between positive and negative classes.

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2.3 Measurement Methods Based on Facial Features

2.3.1 Eye features

The fatigue level of pilots exhibits strong consistency with changes in eye feature parameters, making eye features a core characteristic for fatigue detection.Di Stasi L L In experiments conducted by researchers such as on fatigue state detection, the saccadic amplitude [12], saccadic duration, and peak saccadic velocity of subjects were studied. It was found that these eye features, particularly peak saccadic velocity, are closely related to fatigue levels and can effectively reflect the fatigue state of the subjects. Diaz-Piedra C et al. [13] conducted guided saccade tests and demonstrated that pilots‘ peak saccadic velocity decreased by approximately 3% before and after flight missions. This indicates that pilots‘ fatigue levels can be assessed and predicted by monitoring their peak saccadic velocity. This approach not only improves the efficiency of flight missions but also enhances their safety and accuracy. To further identify the facial features influencing pilots‘ fatigue states, researchers conducted a series of experiments. In these experiments, they recorded and analyzed the relationship between physiological data such as eye movements, facial muscle movements, and fatigue states. By analyzing these data, researchers gained a better understanding of the mechanisms underlying pilot fatigue and proposed improved solutions to ensure flight safety [14]. The PERCLOS standard proposed by Carnegie Mellon Institute provides an objective and reliable method for fatigue detection by defining the proportion of time the eyes remain closed [15, 16].

2.3.2 Mouth features

Pilots often exhibit behaviors such as yawning when fatigued, making mouth features a core indicator for fatigue detection.Wang et al. [17] used projection methods to capture facial displacements and features, particularly around the mouth, and analyzed the degree and duration of mouth opening to determine whether the subject was yawning. Additionally,Adtahi et al. [18] processed information such as facial color and texture to detect facial and mouth regions, aiding in better judgment of yawning and thus more accurately assessing the subject‘s fatigue level.

2.4 Multimodal Data Fusion for Fatigue Analysis

Due to individual differences, human fatigue is a highly complex physical and mental state, and a single physiological feature is insufficient to capture different types of fatigue. Therefore, a novel multidimensional data fusion method was proposed, integrating physiological and facial data to effectively extract multiple types of information, thereby improving the accuracy and reliability of fatigue level recognition.

Multimodal data fusion analysis is an innovative fatigue detection method that comprehensively analyzes pilots‘ driving states and fatigue levels by combining multiple physiological data.Virk et al. [19] compared the detection performance across different modalities and found that multimodal data fusion yielded higher test accuracy than single-modal data, particularly when EEG and ECG were combined, significantly enhancing the robustness of the experiment. The final results showed that the proposed multimodal fusion framework achieved a fatigue detection rate of 92.4% in cross-validation, significantly outperforming single-modal methods (EEG alone achieved 84.7%, and ECG alone achieved 78.3%).Zhaet al. proposed a method based on ECG A multimodal fusion fatigue detection system incorporating video signals utilizes convolutional neural networks and long short-term memory networks for video feature extraction, while combining ECG features based on time-domain and frequency-domain analysis. The system ultimately achieves fatigue state classification through a multimodal feature fusion module. Experimental results demonstrate that the proposed system, after fusing ECG with video signals, achieves a fatigue detection classification accuracy of 94.6%, significantly outperforming single-modal detection methods (with ECG alone reaching 86.3%, and using only video signals achieving 81.5%) [1].

In summary, multidimensional data fusion technology has achieved significant international development and holds vast application prospects.

3. Conclusion

Pilot fatigue detection is a crucial technical research direction for ensuring aviation safety. This paper begins with data collection and analysis of EEG signals, ECG signals, EMG signals, and pilot facial features, verifying the effectiveness of multidimensional data fusion in fatigue detection. The main research contributions of this paper are as follows:

(1) Compared to conventional subjective fatigue detection methods, physiological signal detection (e.g., ECG, EEG, EMG) is more objective and accurate. This study primarily employs the K-nearest neighbors (KNN) and support vector machine (SVM) algorithms for comprehensive classification and analysis of measured physiological data. For ECG signals, heart rate variability indices serve as the core metric, with KNN demonstrating superior accuracy in classifying ECG-based fatigue states. EMG signals are analyzed through muscle signal amplitude and frequency

to determine fatigue levels, where KNN shows greater advantage in distinguishing between positive and negative categories. EEG signals face interference from artifacts during measurement, which can be effectively mitigated using a third-order Butterworth bandpass filter. The study concludes that KNN outperforms SVM for EEG signal analysis.

(2) Beyond internal factors like physiological signals, pilot fatigue can also be assessed using facial features such as eye and mouth characteristics. This paper focuses on utilizing the pilot's peak saccadic velocity to determine fatigue states. Additionally, the PERCLOS standard proposed by Carnegie Mellon University offers a reliable and objective method based on eye closure duration ratio. Monitoring the duration and degree of mouth opening, as well as facial color and texture, further enhances fatigue state judgment.

(3) Compared to analyzing a single physiological feature, the multimodal data fusion method can better distinguish different types of fatigue states, offering high recognition accuracy and reliability. This paper compares the multimodal data fusion method with cases where electrocardiographic (ECG) signals, electroencephalographic (EEG) signals, and video signals are used separately, concluding that the multimodal data fusion method achieves higher classification accuracy. This demonstrates the feasibility of multimodal data fusion in assessing pilot fatigue states.

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