Research on Fatigue Classification of Flight Simulation Training

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Abstract*—Fatigue is an important factor affecting modern flight safety. It can easily lead to a decline in the pilot's operational capabilities, misjudgments and flight illusions. Moreover, it may even cause serious flight accidents. In this paper, a wearable wireless physiological device is used to obtain pilot electrocardiogram data in simulated flight experiments. Bioelectric signals have higher reliability than image information, and are not easily affected by the external environment (such as shooting angle and light intensity). On the other hand, neural networks have been widely used in various classification and regression tasks. In this study, the EEG was collected in the driving flight simulator, and after simple filtering and preprocessing, the time domain data was sent directly to the convolutional neural network, eliminating the need for additional feature extraction operations. We found that the convolutional neural network can effectively amplify the fluctuation details of the time domain data and train the pilot fatigue state recognition model. The results show that the recognition accuracy of the convolutional neural network model reaches 98%, which is 26% and 12% higher than the traditional k-nearest neighbor classification algorithm (KNN) and support vector machine (SVM) model, respectively. The recognition model based on convolutional neural network established in this paper is suitable for the recognition of pilot fatigue status. This has important practical significance for reducing flight accidents caused by pilot fatigue, and provides a theoretical basis for pilot fatigue risk management and the development of intelligent aircraft autopilot systems.

Keywords-Fatigue Classification; Eeg; Cnn; Neural Network

I. INTRODUCTION

International Civil Aviation Organization (ICAO) statistics on global planned commercial flight accidents and casualties in the past ten years show that from 2013 to 2017, the annual number of flight accidents has not changed much, but the number of casualties has been there have been large fluctuations, and the overall number of casualties remains high. In addition, once an accident occurs, the direct loss caused is the production and manufacturing cost of an aircraft (the average value of Boeing's aircraft supplies is approximately $90 million), plus compensation for accident losses. Although the flight accident rate has been on a downward trend in recent decades, the injuries and losses caused by airplane accidents have not changed much. At the same time, every flight accident will cause fatal injuries to every family and indirectly cause national losses. Therefore, aviation safety issues need to be treated strictly for countries in all regions of the world.

According to the flight accident statistics of the Federal Aviation Administration (FAA) and NASA, only 12% of flight accidents are caused by problems with the aircraft itself, and more than 73% of accidents involve human factors. 67% of aircraft accidents caused by mistakes of the aircraft, the most important factor is the pilot's operation error, which accounts for about 51% of the total number of air crashes. The main reason for the pilot's operation error is that the driver is in a state of fatigue and his driving is alert. Degree drops. According to the statistics of road traffic accidents in my country, 90% of traffic accidents are caused by the driver's human factors, which are mainly due to the driver's dangerous

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driving state, such as distracted driving, fatigue driving, etc.

The Current methods for detecting pilot alertness go in three directions, namely aircraft-based behavioural monitoring, pilot behavioural recording and pilot physiological signal measurement. Of these, the first two methods are more influenced by the external environment such as the aircraft model and driving environment, while the latter method depends only on the subject conditions; therefore, it shows a higher ability to detect driver drowsiness. Measurements of physiological signals include neuronal electrical activity from electroencephalography (EEG), eye movements from electrooculography (EOG), heart rate from electrocardiography (ECG), muscle activity from electromyography (EMG) and tissue oxygenation from near infrared spectroscopy (NIRS) [1]. However, of these signals, the EEG signal, which is less likely to be influenced by individual characteristics, has been widely used as the 'gold standard' for fatigue detection and has proved to be a promising method for studying drowsiness and changes in driver alertness.

EEG is the overall response of brain nerve cell electrophysiological activity on the scalp surface or cerebral cortex [2]. According to its frequency, it can be divided into 5 different bands: (1) δ wave (1~4 Hz), which generally only appears when adults are asleep; (2) θ wave (4~8 Hz), which mainly occurs in sleep State; (3) α wave (8~14 Hz), which generally occurs in a relaxed state; (4) β wave (14~30 Hz), the increase in the power spectrum of the β wave is closely related to the increase in alertness. (5) Gamma wave (30-49 Hz).

As early as the 1980s, studies on the correlation between EEG and brain fatigue have been carried out abroad. Relevant studies have shown that EEG is very sensitive to fluctuations in vigilance. EEG will change significantly with changes in vigilance. EEG It can predict the decline of brain performance caused by continuous mental work [3]; in the 1990s, EEG research was further deepened, and people began to pay attention to the changes in various bands of EEG during brain fatigue. Research found the correlation between reduced human alertness and fatigue It will be concretely reflected in different wave bands of EEG, among which the changes of theta wave and alpha wave are particularly obvious [4], which is specifically manifested in the power spectrum of theta wave and alpha wave when people are in a state of fatigue; enter 21 In the century, the research on the different bands of EEG in the state of brain fatigue is more detailed, the θ, α and β frequency bands in EEG and the combined parameters of different frequency bands. For example, Jap et al. [5] conducted a more comprehensive experiment. The four EEG bands of δ, θ, α, β and $(\theta+\alpha)/\beta$, α/β, (θ+ The evaluation of the four parameters of α)/(α+β) and θ/β showed that during the transition from non-fatigue state to fatigue state, the activities of δ wave and θ wave were relatively stable, and the activity of α wave decreased slightly. The β wave activity is significantly reduced; the values of the four combination parameters have increased, among which the increase in $(\theta+\alpha)/\beta$ is more obvious, and the value of $(\theta+\alpha)/\beta$ is also more obvious under different fatigue levels the difference. By combining EEG signals of different bands for analysis, and then proposing suitable combination parameters, not only can the respective characteristics of different bands of EEG signals be fully utilized, but also the detection results can be more accurate and comprehensive through the combination of parameters.

Many domestic scholars have also conducted research on the alertness of drivers by EEG. In addition to the above four combined EEG features, there are also time-domain analysis and frequency-domain analysis of brain waves, power spectral density (PSD), and entropy. Carry out the analysis and evaluation of the driver's alertness from an equal angle. EEG is also an important parameter in human factors engineering. EEG's brain fatigue detection is also widely used in human factors engineering. For example, using the EEG fatigue detection method to evaluate and guide the professional training and psychological adjustment of pilots, it was found that the level of positive emotions of pilots has been improved. Similarly, the brain fatigue detection using EEG can also study the effect of brain fatigue on selective visual attention, and the results show that mental fatigue has a negative impact on the ability of selective visual attention.

At present, the use of EEG can be used to determine the degree of brain fatigue and brain fatigue. With the development of high-throughput EEG technology and the intelligence of EEG data analysis, traceability analysis of high-throughput EEG data is expected to be used for brain fatigue location analysis; on the other hand, the fusion of synchronous EEG and functional magnetic resonance imaging technology also provides technical support for brain fatigue location analysis. In short, EEG-based brain fatigue detection will develop in the direction of quantitative, precise, and accurate positioning, and the fatigue detection ability and credibility of drivers will also continue to improve.

II. MATERIALS

A. Experimental design

There is a certain gap between the difficulty and the degree of danger in simulated flight driving and real driving. In order to reduce the impact of new and veterans on driving task control ability and ensure the objectivity of test data, 20 graduate students are selected, aged 24-28 years old (Average age 26.8 years), healthy, all right-handed; no driving experience; no drugs taken during the test; no alcoholic foods were consumed 24 hours before the test, and no caffeine-containing beverages were consumed 12 hours before the test. Did not eat and exercise vigorously in the first 1 hour; in order to avoid the impact of the test period, the test was completed within a similar period of the human body's physiological cycle; 1 day before the test, the subjects were trained on the driving simulator operation for 20 minutes, and try to ensure that the samples are correct The sameness and equality of driving proficiency. Participants were informed of the specific content of the experiment to ensure that they fully understand how the physiological data collected during the study will be used. Every participant is willing to participate in the experiment; the experimental data must eliminate personal identification information, and only retain data that has a specific impact on the experiment. The research is carried out at noon (12:00-14:00), and the indoor temperature is controlled at 25±2℃ [6], the indoor humidity is 45±10% [7]. All participants were required to perform moderate mental work within 5 hours before the experiment to reduce nerve excitability. They are not allowed to participate in any form of physical labor to prevent changes in blood pressure and heart rate. Each participant had 8-9 hours of sleep before the experiment. The observer is set to record the state of the experimenter, including whether there are red blood streaks in the eyes and changes in blinking frequency [8]. The neural network model uses the Tensorflow GPU 2.4.0 framework, the CUDA version is 11.0, and the cuDNN version is 8.0. We use 4 NVIDIA Titan V graphics cards to accelerate the training process.

B. Experiment procedure

The experimental stimulus is presented on a 31.5-inch desktop curved display. The interactive objects on the screen are the "Microsoft Flight Simulator X: Steam Edition" game published by Dovetail Games and developed by aviation expert Jane Whittaker. This game allows non-professional players to feel the pilot's nervousness when encountering an emergency. The graphics and the degree of realism have reached the peak, and the various elements encountered in real-world flight, such as aerodynamics, weather, and geography The environment, flight control system, flight electronic system, combat flight weapon system, ground flight guidance, etc., are comprehensively simulated in the computer, and the flight simulation control and flight sensory feedback through external hardware equipment are used to feedback the fatigue expression of the pilot in the previous year. On the basis of, eye movement, line of sight, etc., complete the EEG acquisition and analysis of pilot training subjects (takeoff, landing), identify the emotional characteristics of pilots during training, complete multi-dimensional channel data fusion, and build pilot control response The mathematical model of time and attention distribution monitors and evaluates the effect of flight training and conducts control experiments. Before entering the simulated control environment, the subject should wear the EEG device to ensure that the device is connected to the software to measure resistance (the Ergo software displays the port is green), and the Ergo software will display the connection status of the port. There are four types: 1. Green: The port is connected normally and the signal is stable 2. Orange: The port is connected normally and the signal is unstable 3. Red: The port is connected normally and the signal is weak 4. Gray: No signal at the port before the experiment, it is necessary to ensure that the device and the software are properly connected to measure the resistance (all ports are green), and blink and close the eyes to confirm that the device is receiving the eyeballs normally. After the test subjects enter the simulated flight environment, they need to continuously interact with the experimental materials and retrograde within half an hour to complete the take-off and landing of the fixed-wing aircraft, fly around the field five times, and fly on the designated route. In the formal test process, the subjects need to enter the simulated maneuvering scene (as shown in Figure 1), and the flight simulation platform simulates the experimental task of driving.

Figure 1. Simulated driving environment

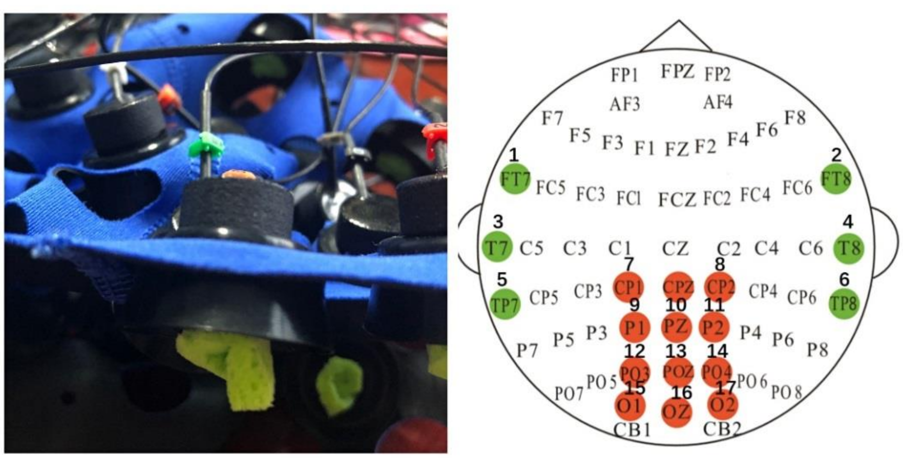

Figure 2. EEG acquisition equipment

During the execution of the task, random pop-up windows will appear within the subject's field of vision, and the subject needs to move the point of sight to the pop-up window to close the window. The time interval from when the pop-up window appears to when it closes is the reaction time. Based on the response time, the research team developed a mental label (fatigue/mental) for the EEG signals within 10s before the pop-up window appeared. One set of experiments is set for half an hour. Because the EEG cap will affect the subjects, too long time will increase the subject's eye height and cause extreme discomfort. Therefore, this topic divides a set of experiments into two Second, the specific timetable is shown in Table 1.

TABLE I. EXPERIMENT SCHEDULE

Participant ID	**001**	**002**	**003**
Experiment 101	9:00-9:30	10:00-10:30	11:00-11:30
Experiment 102	13:30-14:00	14:30-15:00	15:30-16:00

During the completion of the task, restrict the subjects' body and head to more vigorous movements. Moreover, before the start of the experiment, the recorder will tell the subjects that the eye-closing behavior should be spontaneous rather than deliberate, such as allowing eyes to be closed when they feel sleepy or uncomfortable. Since there is no actual threat to personal safety, subjects will go along with it when they are fatigued. These situations are difficult to obtain in a real manipulation environment. This helps us to investigate the characteristics of changes in physiological signals when the human body is fatigued.

III. TECHNICAL ROUTE

Carlo Matteucci et al [13]. First obtained the muscle nerve electrical signal with a galvanometer in 1881 and established the concept of neurophysiology. In the following nearly a hundred years, people gradually clarified the collection methods and standards of bioelectric signals. The non-invasive collection methods that have been widely used in the field of EEG signals include EEG, magnetic resonance imaging, near-infrared spectroscopy, and there are four kinds of magnetic EEG [14]. Among them, the multi-channel electrode EEG method, which integrates high time resolution, low cost, and non-invasive safety, is the most widely used. Thanks to the continuous advancement of technology, the 10-20 standard lead, 10-10 standard lead and 10-5 standard lead established by the American Society of Clinical Neurophysiology are the most common in clinical trials [15]. The three standard system guides are extensions of each other and keep the same overlap in the naming rules. This simplifies the EEG signal research process and reduces the difficulty of technical communication. It also clears the obstacles for the electrode naming rules for this study. Specific electrode naming and the spatial coordinates can be queried on the website of the American Society of Clinical Neurophysiology, and will not be listed in detail here. In this project, the electrode position recommended by the 10-10 standard lead system will be used as a benchmark to start the experiment.

The EEG signal is a sign of neural activity. The neural activity generated by any part of the human body will be more or less reflected in the EEG signal [16], and the research needs to focus on the "event potential", that is, the human brain because of a certain One or some physiological electrical signals generated by certain activities, so choosing a suitable reference electrode according to different research focuses will greatly reduce the research workload. The research of Lei Xu et al. [17, 18] showed that the reference electrode is the key to the study of EEG and event-related potentials. Since Yao et al. proposed the reference electrode standardization technology in 2001, REST has quickly become the first choice for most EEG research models. In addition, in some cases, the full electrode average can also be considered to have the same effect as REST. Essl et al. suggested choosing FCz electrode as a reference electrode when the results of the study are not clear. The consistency based on FCz electrode is higher than the consistency based on non-cranial reference, and their research has become part of REST. Yao Dezhong et al. studied the influence of different reference electrodes on spectrum mapping. REST technology aims to build a bridge between traditional reference electrodes (such as scalp or average reference) and theoretical zero reference. The reference point at infinity has a theoretical neutral potential and is regarded as an approximate zero potential point in REST.

EEG signal is a 5-100μV low-frequency bioelectric signal, which needs to be amplified before it can be displayed and processed. An important operation in signal processing and interpretation is filtering. The main function of filtering is to remove interference signals from EEG signal data. Especially for high-frequency signals caused by the external environment, the filtering used in EEG signal processing is mainly divided into high-pass filtering, low-pass filtering and notch filtering. The filtered data can be analyzed for characteristics. There are two main characteristics of EEG data: spatial characteristics and time-frequency characteristics. High-pass filtering aims to pass signals above a limited frequency without attenuation, while blocking and attenuating signals below the limited frequency. Since the EEG is a signal of about 30 Hz, and the frequency above 50 Hz is only involved in the medical diagnosis of epilepsy and human brain physiology, high-pass filtering is rarely used in EEG signals, but some scholars choose to do it. The high-pass filter of 0.1~0.7Hz is designed to remove frequency components with extremely low interference such as breathing. If there is a problem of baseline drift in the signal, Alste et al. conducted a study on ECG and suggested using high-pass filtering to deal with such problems. Although high-pass filtering may be one of the means to solve the baseline drift, Acunzo et al. found that high-pass filtering can cause early ERP and ERF system deviations. High-pass filtering is used cautiously when dealing with the model of EEG and ERP signal fusion.

Low-pass filtering allows signals with frequencies below a certain range to pass, and signals above the critical frequency are blocked and attenuated. Because the EEG signal acquisition instrument is sensitive to weak electrical signals, and the frequency of the mains power in my country is around 50Hz, although there is still a certain frequency space below 30Hz from the target, low-pass filtering must be performed to reduce the impact of the mains signal on the data. This operation is also one of the normal operations in EEG signal processing.

McFarland et al. in 1997 proposed a spatial filter selection based on EEG, by selecting different filters to process the signal to obtain a clear EEG signal. When studying EEG signals, Higashi et al. found that the spatial filter based on the common space pattern method of electrode weights is very effective in the classification of EEG signals based on moving images, but the existing methods have certain limitations. For this reason, a discriminative filter bank is proposed to extract the bands related to the brain activity of moving images.

The time-frequency domain method is also a common EEG signal research method. Hjorh, Salinsky and Valdes discussed the reliability of EEG frequency domain analysis. An important step in time-frequency analysis is to convert time-domain signals into frequency-domain signals. If the signal is statistically stable, or there is a fixed law, then the finite length signal can be transformed into a frequency form by using a linear transformation.

IV. METHODS

EEG data analysis involves a variety of signal processing techniques, including but not limited to signal acquisition, preprocessing, and feature extraction. There are also a variety of methods that are widely used in data classification, such as KNN based on sample feature distance and VC theory. Linear SVM and models based on convolutional neural networks. This chapter will respectively introduce the key technologies of the above three fields involved in this research.

EEG signal processing is mainly composed of signal acquisition, conversion reference, filtering, artifact removal, segmentation, independent component analysis and other operations. In addition, you can also choose whether to downsample the collected data according to the actual situation, but you need to pay attention if it is down-sampling, it may be necessary to perform linear or non-linear interpolation to complement the disappeared features. This article mainly extracts the four features of EEG δ, θ, α, β for fatigue classification.

A. K-Nearest Neighbor

The K-Nearest Neighbor (KNN) algorithm is one of the commonly used classification algorithms. When there is little or no prior knowledge of the data distribution, KNN should be the preferred method. Cover et al [9]. Made it clear that the upper limit of the classification error of the KNN algorithm is twice that of the Bayesian classification error. The algorithm aims to calculate the feature distance between the unknown sample and the known sample group, and infer the category of the unknown sample based on the distance. Common distances include Euclidean Distance, Minkowski Distance, Manhattan Distance, Chebyshev Distance, etc.

Euclidean distance is the most common measurement method, which measures the absolute distance between points in a multidimensional space, and is defined as follows.

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{1}$$

Since the Euclidean distance is calculated based on the absolute value of the features of each dimension, the premise of using the Euclidean distance is to ensure that the dimensions of the indicators have the same dimension. Different dimensions may cause the Euclidean distance to be invalid. The Mind distance is the Euclidean distance. The generalization of, the current p=2 in the following formula is the Euclidean distance.

$$d(x,y) = \left(\sum_{i=1}^{n}|x_i - y_i|^p\right)^{1/p} \tag{2}$$

The Manhattan distance is derived from the city block distance. The result of summing the distances in multiple dimensions, that is, when p=1 in the formula, the Manhattan distance is obtained.

$$d(x,y) = \sum_{i=1}^{n}|x_i - y_i| \tag{3}$$

In addition, feature conversion can also improve the accuracy of the model to a certain extent [10]. Commonly used feature transformations include standardization and fuzzification. Standardization eliminates the influence of different scales in the same dimension state, and fuzzification uses the uncertainty of eigenvalues to improve performance. The fuzzification of features in the field of EEG data analysis can show better performance in KNN. Yang et al [1]. Conducted a detailed discussion on the effect of distance measurement, and came to the conclusion: Compared with simply using Euclidean distance, designing the distance measurement according to the actual situation will greatly improve the accuracy of KNN classification.

B. Support Vector Machine

Support vector machines are one of the commonly used tools in machine learning. Compared with deep neural networks, support vector machines are particularly good at handling situations where feature dimensions are more than the number of samples. In the field of small samples, support vector machines are better than deep neural networks. Select [13]. The linear support vector machine aims to find a hyperplane far away from all types of samples. When the sample has random disturbances, the hyperplanes far away from the sample have a strong tolerance for the disturbance, making SVM not easy to over-fit combine. The essence of linear SVM is a convex quadratic programming problem.

$$\mathrm{argmax}_{w,b}\left(\min_i \frac{2}{\|w\|}|w^T x_i + b|\right) \tag{4}$$

Among them, w, b are the vector of the weight and offset of the hyperplane. At this time, the learning goal of SVM is to find a suitable set of w, b values, so that the planning problem can be solved.

C. Convolutional Neural Network

According to the characteristics of EEG, a two-dimensional convolutional neural network is used in the design of the neural network. In the experiment, the data set was randomly divided into training set and test set at a ratio of 8:2, and then a neural network structure was established for training on EEG features. The training iterations were 50 times, and the learning rate was set to 0.001. Through the analysis of the experimental results, the loss rate and accuracy curves of the training set and test set of EEG feature training are shown in Figure 3 and Figure 4. In the traditional fatigue detection method SVM, the average accuracy of KNN is 86%and 72% respectively. Compared with the traditional fatigue detection method, the convolutional neural network method has indeed improved a lot, especially the convolutional neural network method proposed in this paper can achieve 98%.

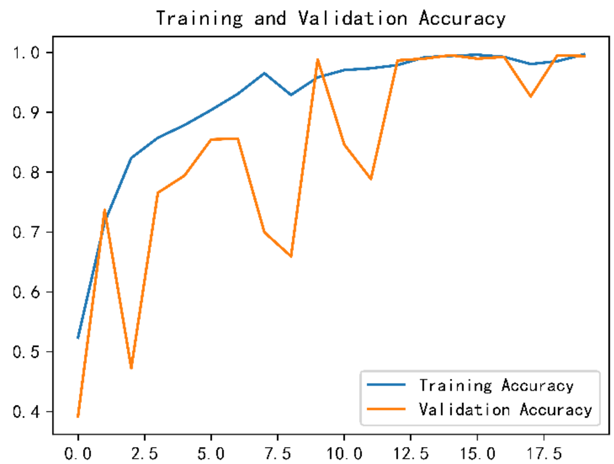

Figure 3. Accuracy of training set and test set

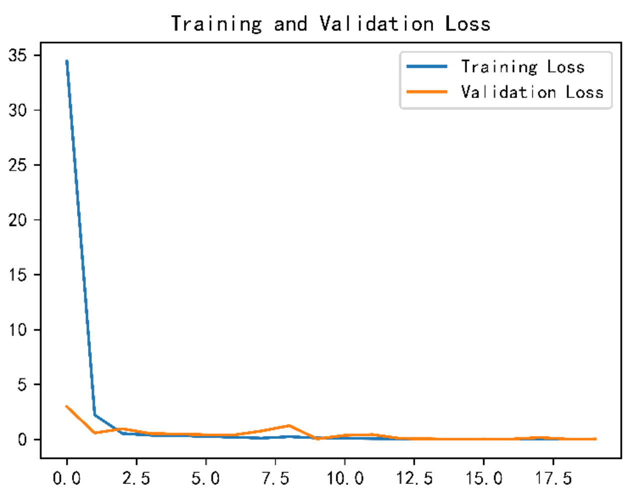

Figure 4. Loss rate of training set and test set

V. CONCLUSION

The detection of fatigue state is widely used in life, and the judgment of fatigue state is helpful to the safe operation of the operator, can reduce the occurrence of accidents, and protect the physical and mental health of the operator. In order to further verify the effectiveness of the method in identifying fatigue classification, the method in this paper is compared with traditional K nearest neighbors, support vector machines and the current more popular deep learning methods. The classification and recognition accuracy rates of KNN, SVM and CNN reached 72% respectively. , 86% and 98%, the accuracy of the method in this paper reaches 98%, which better realizes the operator's fatigue classification. Carry out operator fatigue classification, the classification accuracy rate reaches 98%, and the fatigue state classification is well realized. At the same time, the complex feature extraction process in traditional algorithms is avoided, which is beneficial to real-time and accurate detection of operator fatigue. In addition, applying the same model to different subjects, the classification accuracy rate of each subject's fatigue state exceeds 93%, which can better eliminate the influence of individual differences.

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飞行模拟训练的疲劳分类研究

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***摘要—*疲劳是影响现代飞行安全的重要因素。很容易导致飞行员操作能力下降、误判和飞行幻觉。而且，它甚至可能导致严重的飞行事故。本文采用可穿戴无线生理设备在模拟飞行实验中获取飞行员心电图数据。生物电信号比图像信息具有更高的可靠性，不易受外界环境（如拍摄角度、光照强度等）的影响。另一方面，神经网络已广泛用于各种分类和回归任务。本研究将脑电图采集在驾驶飞行模拟器中，经过简单的滤波和预处理后，将时域数据直接发送到卷积神经网络，无需额外的特征提取操作。我们发现卷积神经网络可以有效放大时域数据的波动细节，训练飞行员疲劳状态识别模型。结果表明，卷积神经网络模型的识别准确率达到了 98%，分别比传统的 k 近邻分类算法（KNN）和支持向量机（SVM）模型提高了 26%和 12%。本文建立的基于卷积神经网络的识别模型适用于飞行员疲劳状态的识别。这对于减少飞行员疲劳造成的飞行事故具有重要的现实意义，为飞行员疲劳风险管理和智能飞机自动驾驶系统的发展提供了理论依据。**

关键词-疲劳分类; 脑电; 卷积网络;神经网络

1. 背景

国际民航组织(ICAO)过去十年全球计划商业飞行事故和人员伤亡的统计数据显示,2013 年至 2017 年,每年的飞行事故数量变化不大,但伤亡人数却一直很大波动较大,总伤亡人数居高不下。此外,一旦发生事故,造成的直接损失是飞机的生产和制造成本(波音飞机用品的平均价值约为 9000 万美元),加上事故损失的赔偿。尽管近几十年来飞行事故发生率呈下降趋势,但飞机事故造成的伤害和损失并没有太大变化。同时,每一次飞行事故都会给每个家庭造成致命的伤害,间接造成国家损失。因此,全球各个地区的国家都需要严格对待航空安全问题。根据美国联邦航空局(FAA)和美国宇航局的飞行事故统计,只有12%的飞行事故是由飞机本身的问题造成的,超 73%的事故涉及人为因素。67%的飞机事故是由飞机失误造成的,其中最主要的因素是飞行员的操作失误,约占空难总数的51%。飞行员操作失误的主要原因是驾驶员处于疲劳状态,驾驶时警觉。学位下降。据我国道路交通事故统计,90%的交通事故是由驾驶员的人为因素造成的,主要是由于驾驶员的危险驾驶状态,如分心驾驶、疲劳驾驶等。

目前检测飞行员警觉性的方法主要分为三个方向,即基于飞机的行为监测、飞行员行为记录和飞行员生理信号测量。其中,前两种方法受机种、驾驶环境等外界环境影响较大,后一种方法仅取决于主体条件;因此,它显示出更高的检测驾驶员睡意的能力。生理信号的测量包括来自脑电图(EEG)的神经元电活动、来自眼电图(EOG)的眼球运动、来自心电图(ECG)的心率、来自肌电图(EMG)的肌肉活动和来自近红外光谱(NIRS)的组织氧合[1]。然而,在这些信号中,不太可能受个体特征影响的EEG信号已被广泛用作疲劳检测的"黄金标准",并已被证明是研究困倦和驾驶员警觉性变化的一种很有前途的方法.

脑电图是脑神经细胞电生理活动对头皮表面或大脑皮层的整体反应[2]。按其频率可分为 5 个不同波段:(1)δ 波(1~4Hz),一般只在成人睡着时出现;(2)θ 波(4~8Hz),主要发生在睡眠状态;(3)α 波(8~14Hz),一般出现在松弛状态;(4)β 波(14~30Hz),β 波功率谱的增加与警觉性的增加密切相关。

早在 1980 年代,国外就已经开展了脑电图与脑疲劳相关性的研究。相关研究表明,脑电图对警觉性的波动非常敏感。脑电图会随着警惕性的变化而发生显着变化。EEG 可以预测持续脑力劳动导致的大脑性能下降[3];1990 年代,脑电图研究进一步深入,人们开始关注脑疲劳时脑电图各波段的变化。研究发现人体警觉性降低与疲劳的相关性会具体体现在脑电图的不同波段,其中θ波和α波的变化尤为明显[4],具体表现在θ波的功率谱上和人处于疲劳状态时的α波;进入 21 世纪,对脑疲劳状态下脑电图不同频段的研究更加细致,脑电图中的 θ、α、β 频段以及不同频段的组合参数。例如,日本等人[5]进行了更全面的实验。δ,θ,α,β 和(θ+α)/β,α/β, (θ+α)/(α+β)和θ/β 四个参数的 EEG 四个波段的评估表明,在从非疲劳状态到疲劳状态的过渡,δ 波和 θ 波的活动相对稳定,α 波的活动略有下降。β 波活动明显降低;4 个组合参数的值都有所增加,其中(θ+α)/β 的增加更为明显,(θ+α)/β 的值在不同疲劳等级下的差异也更为明显。通过对不同频段的脑电信号进行组合分析,然后提出合适的组合参数,不仅可以充分利用不同频段的脑电信号各自的特点,而且通过参数的组合,检测结果可以更加准确和全面。

国内很多学者也对 EEG 对驾驶员的警觉性进行了研究。除了上述四种组合的脑电图特征外,还有脑电波、功率谱密度(PSD)和熵的时域分析和频域分析。对驾驶员的警觉性进行同等角度的分析评价。脑电图也是人因工程中的一个重要参数。EEG 的脑疲劳检测在人因工程中也有广泛的应用。例如,利用脑电疲劳检测方法对飞行员的专业训练和心理调整进行评估和指导,发现飞行员的积极情绪水平有所提高。同样,使用EEG进行脑疲劳检测也可以研究脑疲劳对选择性视觉注意的影响,结果表明精神疲劳对选择性视觉注意能力有负面影响。

目前使用脑电图可以判断脑疲劳程度和脑疲劳程度。随着高通量脑电技术的发展和脑电数据分析的智能化,高通量脑电数据的溯源分析有望用于脑疲劳定位分析;另一方面,同步脑电图与功能磁共振成像技术的融合也为脑疲劳定位分析提供了技术支持。总之,基于 EEG 的脑疲劳检测将朝着定量化、精准化、精准定位的方向发展,驾驶员的疲劳检测能力和可信度也将不断提升。

2. 实验

2.1 实验设计

模拟飞行驾驶与真实驾驶的难度和危险程度存在一定差距。为减少新老学员对驾驶任务控制能力的影响,保证测试数据的客观性,选取 20 名研究生,年龄 24-28 岁(平均年龄 26.8 岁),身体健康,都是右撇子;没有驾驶经验;测试期间没有服用任何药物;测试前 24 小时未食用酒精食物,测试前 12 小时未食用含咖啡因的饮料。前 1 小时没有吃东西和剧烈运动;为避免测试周期的影响,测试在与人体生理周期相近的周期内完成;考试前 1 天,对受试者进行驾驶模拟器操作 20 分钟的培训,并尽量保证样本正确、驾驶水平的相同性和平等性。参与者被告知实验的具体内容,以确保他们充分了解在研究期间收集的生理数据将如何被使用。每个参与者都愿意参与实验;实验数据必须剔除个人身份信息,只保留对实验有特定影响的数据。研究在中午(12:00-14:00)进行,室内温度控制在 25±2℃[6],室内湿度为 45±10%[7]。要求所有参与者在实验前 5 小时内进行适度的脑力劳动,以降低神经兴奋性。他们不允许参加任何形式的体力劳动,以防止血压和心率的变化。每个参与者在实验前都有 8-9 小时的睡眠时间。观察者被设置为记录实验者的状态,包括眼睛是否有红血丝和眨眼频率的变化[8]。神经网络模型采用 Tensorflow GPU 2.4.0 框架,CUDA 版本为 11.0,cuDNN 版本为 8.0。我们使用 4 块 NVIDIA Titan V 显卡来加速训练过程。

2.2 实验流程

实验刺激呈现在31.5英寸桌面曲面显示器上。屏幕上的互动对象是由 Dovetail Games 发行、航空专家 Jane Whittaker 开发的《微软飞行模拟器 X:Steam 版》游戏。这款游戏可以让非职业玩家在遇到紧急情况时感受到飞行员的紧张情绪。画面和逼真程度达到了巅峰,现实飞行中遇到的各种元素,如空气动力学、天气、地理环境、飞行控制系统、飞行电子系统、作战飞行武器系统、地面飞行制导等在计算机中进行综合模拟,通

过外部硬件设备进行飞行模拟控制和飞行感官反馈,反馈飞行员上一年的疲劳表现。以眼动、视线等为基础,完成飞行员训练科目(起飞、着陆)的脑电采集与分析,识别飞行员训练过程中的情绪特征,完成多维通道数据融合,构建飞行员控制响应时间和注意力分布的数学模型监控和评估飞行训练的效果并进行控制实验。进入模拟控制环境前,被试需佩戴脑电设备,确保设备与软件连接进行电阻测量(Ergo 软件显示端口为绿色),Ergo 软件会显示端口的连接状态.有四种:1.绿色:端口连接正常,信号稳定 2.橙色:端口连接正常,信号不稳定 3.红色:端口连接正常,信号弱 4.灰色:实验前端口无信号,需确保设备与软件连接正常,测量电阻(所有端口均为绿色),并眨眼闭眼确认设备正在接收眼球一般。测试对象进入模拟飞行环境后,需要在半小时内不断与实验材料交互并逆行,完成固定翼飞机的起降,绕场飞行五圈,继续飞行指定的路线。在正式测试过程中,受试者需要进入模拟机动场景(如图 1),飞行模拟平台模拟驾驶的实验任务。

图 1 模拟飞行环境

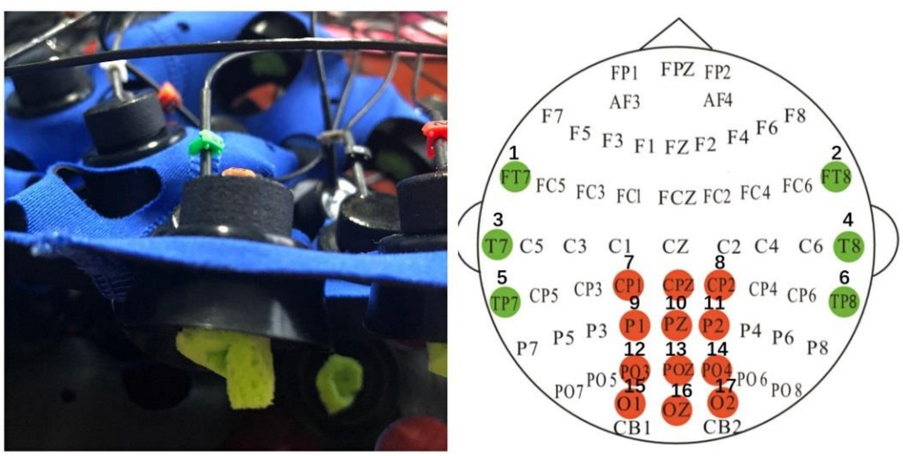

图 2 脑电设备

任务执行过程中,被试视野范围内会随机出现弹窗,被试需要将视点移至弹窗关闭窗口。从弹出窗口出现到关闭的时间间隔就是反应时间。根据响应时间,研究团队在弹出窗口出现前 10

秒内为脑电信号开发了一个心理标签(疲劳/心理)。一组实验设置半小时。因为脑电帽会影响被试,时间过长会增加被试眼高,造成极度不适。因此,本课题将一组实验分为两部分,具体时间表如表 1 所示。

表 1 实验计划表

Participant ID	001	002	003
Experiment 101	9:00-9:30	10:00-10:30	11:00-11:30
Experiment 102	13:30-14:00	14:30-15:00	15:30-16:00

在完成任务期间,限制受试者的身体和头部进行更剧烈的运动。而且,在实验开始前,记录仪会告诉被试,闭眼的行为应该是自发的,而不是刻意的,比如在感到困倦或不舒服的时候让眼睛闭上。由于对人身安全没有实际威胁,因此对象在疲劳时会顺其自然。这些情况在真实的操作环境中是很难获得的。这有助于我们研究人体疲劳时生理信号变化的特征。

3. 技术路线

Carlo Matteucci 等人[13]。1881 年首先用电流计获得肌肉神经电信号,确立了神经生理学的概念。在接下来的近一百年里,人们逐渐明确了生物电信号的采集方式和标准。已广泛应用于脑电信号领域的无创采集方法包括脑电图、磁共振成像、近红外光谱法,磁脑电图有四种[14]。其中,集时间分辨率高、成本低、无创安全于一体的多通道电极脑电图方法应用最为广泛。由于技术的不断进步,美国临床神经生理学会制定的 10-20 标准导联、10-10 标准导联和 10-5 标准导联在临床试验中最为常见[15]。这三个标准系统指南是彼此的扩展,并且在命名规则中保持相同的重叠。这简化了脑电信号研究过程,降低了技术交流的难度。也为本研究扫清了电极命名规则的障碍。具体的电极命名和空间坐标可以在美国临床神经生理学会网站上查询,这里不再详述。本项目以 10-10 标准导联系统推荐的电极位置为基准开始实验。

EEG 信号是神经活动的标志。人体任何部位所产生的神经活动都会或多或少地反映在脑电信号中,研究需要重点关注“事件电位”,即人脑因某一个或某些活动产生的一些生理电信号,因此根据不同的研究重点选择合适的参比电极将大大减少研究工作量。徐磊等人的研究。[17,18]表明参考电极是脑电图和事件相关电位研究的关键。由于姚等人。2001 年提出参比电极标准化技术,REST 迅速成为大多数脑电图研究模型的首选。此外,在某些情况下,全电极平均也可以认为具有与 REST 相同的效果。埃斯尔等人。建议在研究结果不明确时选择 FCz 电极作为参比电极。基于 FCz 电极的一致性高于基于非颅参考的一致性,他们的研究已成为 REST 的一部分。姚德中等。研究了不同参比电极对光谱映射的影响。REST 技术旨在在传统参考电极(如头皮或平均参考电极)和理论零参考电极之间架起一座桥梁。无穷远处的参考点具有理论中性电位,在 REST 中被视为近似零电位点。

脑电信号是 5-100μV 的低频生物电信号,需要经过放大才能显示和处理。信号处理和解释中的一个重要操作是滤波。滤波的主要作用是去除脑电信号数据中的干扰信号。特别是对于外部环境引起的高频信号,脑电信号处理中使用的滤波主要分为高通滤波、低通滤波和陷波滤波。可以分析过滤后的数据的特征。EEG 数据有两个主要特征:空间特征和时频特征。高通滤波旨在使高于有限频率的信号无衰减地通过,同时阻止和衰减低于有限频率的信号。由于 EEG 是 30Hz 左右的信号,而 50Hz 以上的频率只涉及癫痫的医学诊断和人脑生理,因此 EEG 信号很少使用高通滤波,但也有学者选择这样做。0.1~0.7Hz 的高通滤波器设计用于去除呼吸等干扰极低的频率成分。如果信号中存在基线漂移问题,Alste 等人。对心电图进行了研究,并建议使用高通滤波来处理此类问题。尽管高通滤波可能是解决基线漂移的方法之一,但 Acunzo 等人。发现高通滤波会导致早期的 ERP 和 ERF 系统偏差。在处理脑电图和 ERP 信号融合模型时,谨慎使用高通滤波。

低通滤波允许频率低于一定范围的信号通过,高于临界频率的信号被阻挡和衰减。因为脑电信号采集仪对微弱的电信号比较敏感,而我国市电频率在50Hz 左右,虽然距离目标 30Hz 以下还有一定的频率空间,但必须进行低通滤波以

降低 电源信号对数据的影响。该操作也是脑电信号处理中的常规操作之一。

麦克法兰等人。1997 年提出了一种基于 EEG 的空间滤波器选择,通过选择不同的滤波器对信号进行处理,得到清晰的 EEG 信号。在研究 EEG 信号时,Higashi 等人。发现基于电极权重的公共空间模式方法的空间滤波器在基于运动图像的脑电信号分类中非常有效,但现有方法存在一定的局限性。为此,提出了一种判别滤波器组来提取与运动图像的大脑活动相关的频带。

时频域法也是一种常见的脑电信号研究方法。Hjorh、Salinsky 和 Valdes 讨论了 EEG 频域分析的可靠性。时频分析的一个重要步骤是将时域信号转换为频域信号。如果信号在统计上是稳定的,或者有一个固定的规律,那么可以通过线性变换将有限长度的信号变换为频率形式。

4. 研究方法

EEG 数据分析涉及多种信号处理技术,包括但不限于信号采集、预处理和特征提取。还有多种方法被广泛应用于数据分类,如基于样本特征距离的 KNN 和 VC 理论。线性 SVM 和基于卷积神经网络的模型。本章将分别介绍本研究涉及的上述三个领域的关键技术。

脑电信号处理主要由信号采集、转换参考、滤波、去伪影、分割、独立分量分析等操作组成。此外,还可以根据实际情况选择是否对采集的数据进行下采样,但需要注意的是,如果是下采样,可能需要进行线性或非线性插值来补充消失的特征。本文主要提取 EEG 的 δ、θ、α、β 四个特征进行疲劳分类。

4.1 K 最近邻法

K 最近邻(KNN)算法是常用的分类算法之一。当对数据分布知之甚少或没有先验知识时,KNN 应该是首选方法。Cover 等人[9]。明确了 KNN 算法的分类误差上限是贝叶斯分类误差的两倍。该算法旨在计算未知样本与已知样本组之间的特征距离,并根据距离推断未知样本的类别。常见的距离有欧几里得距离、闵可夫斯基距离、曼哈顿距离、切比雪夫距离等。

欧式距离是最常用的测量方法,它测量多维空间中点之间的绝对距离,定义如下。

$$d(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \tag{1}$$

由于欧氏距离是根据各维度特征的绝对值计算的,所以使用欧氏距离的前提是要保证指标的维度具有相同的维度。不同的维度可能会导致欧式距离无效。心灵距离是欧几里得距离。概括来说,下式中的当前 p=2 就是欧几里得距离。

$$d(x,y)=\left(\sum_{i=1}^{n}|x_i-y_i|^p\right)^{1/p} \tag{2}$$

曼哈顿距离源自城市街区距离。多维距离求和的结果，即公式中 p=1 时，得到曼哈顿距离。

$$d(x,y)=\sum_{i=1}^{n}|x_i-y_i| \tag{3}$$

此外，特征转换还可以在一定程度上提高模型的准确性［１０］。常用的特征变换包括标准化和模糊化。标准化消除了同一维度状态下不同尺度的影响，而模糊化则利用特征值的不确定性来提高性能。ＥＥＧ数据分析领域的特征模糊化可以在ＫＮＮ中表现出更好的性能。杨等人［１］。对测距的效果进行了详细的讨论，得出结论：与单纯使用欧式距离相比，根据实际情况设计测距大大提高ＫＮＮ分类的准确率。

4.2 支持向量机

支持向量机是机器学习中常用的工具之一。与深度神经网络相比,支持向量机特别擅长处理特征维度大于样本数量的情况。在小样本领域,支持向量机优于深度神经网络。选择[13]。线性支持向量机旨在找到一个远离所有类型样本的超平面。当样本有随机扰动时,远离样本的超平面对扰动有很强的容忍度,使得 SVM 不容易过拟合组合。线性支持向量机的本质是一个凸二次规划问题。

$$\text{argmax}_{w,b}\left(\min_i \frac{2}{\|w\|}|w^T x_i+b|\right) \tag{4}$$

其中,w,b 为超平面的权重和偏移量的向量。此时 SVM 的学习目标是找到一组合适的 w,b 值,从而解决规划问题。

4. 3 神经网络

根据脑电图的特点，在神经网络的设计中采用了二维卷积神经网络。实验中，将数据集以 8:2 的比例随机分为训练集和测试集，然后建立神经网络结构进行脑电特征训练。训练迭代次数为 50 次，学习率设置为 0.001。通过对实验结果的分析，EEG 特征训练的训练集和测试集的损失率和准确率曲线如图 3 和图 4 所示。在传统的疲劳检测方法 SVM 中，KNN 的平均准确率为 86%和 72%。与传统的疲劳检测方法相比，卷积神经网络方法确实提升了很多，尤其是本文提出的卷积神经网络方法可以达到 98%。

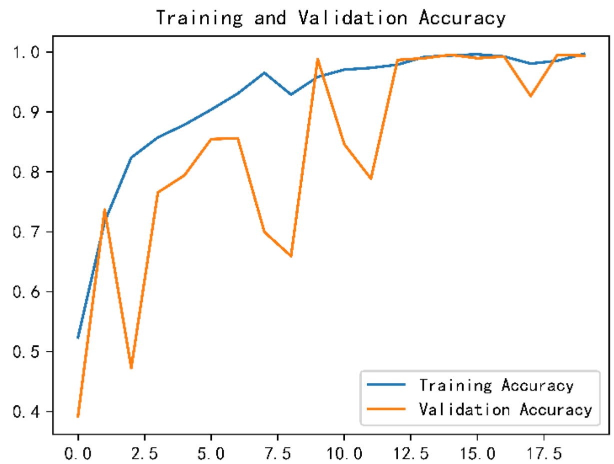

图 3 训练集和测试集的准确率

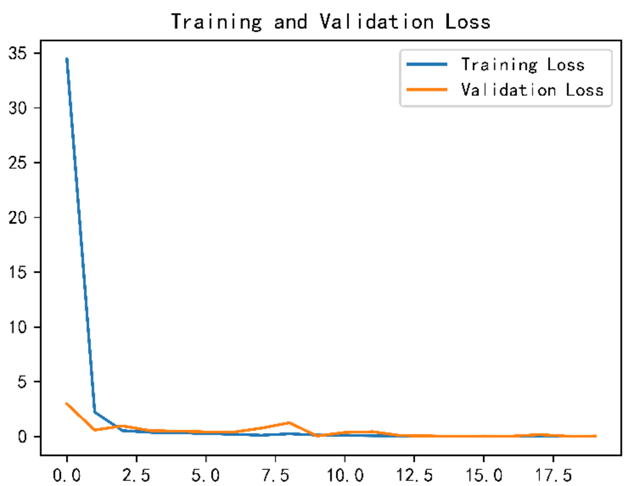

图 4 训练集和测试集的损失率

5. 结论

疲劳状态的检测广泛应用于生活中,疲劳状态的判断有助于操作者的安全操作,可以减少事故的发生,保护操作者的身心健康。为了进一步验证该方法在识别疲劳分类方面的有效性,本文将本文方法与传统的 K 近邻、支持向量机以及目前比较流行的深度学习方法进行了对比。KNN、SVM 和 CNN 的分类和识别准确率分别达到 72%。,86%和 98%,本文方法的准确率达到 98%,较好地实现了操作者的疲劳分类。进行操作员疲劳分类,分类准确率达到 98%,很好地实现了疲劳状态分类。同时避免了传统算法中复杂的特征提取过程,有利于实时、准确地检测操作者的疲劳。此外,将相同的模型应用于不同的受试者,每个受试者疲劳状态的分类准确率超过 93%,可以更好地消除个体差异的影响。

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