Multimodal Approach for Pilot Mental State Detection

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The safety of flight operations depends on the cognitive abilities of pilots. The process of identifying mental states typically involves four steps: collecting data, cleaning it, selecting relevant features, and making predictions. The first step involves capturing signals from the brain and converting them into digital form. Then, to ensure accurate analysis, any extraneous noise or artifacts present in the data are removed through preprocessing. Next, specific characteristics of the data are selected and extracted in preparation for classification. These extracted features are then used by a classifier to make predictions about which class the data belongs to. As this process specifically relates to electrocardiogram (ECG) data, the following provides a summary of previous research on the three stages of mental state detection: preprocessing, feature extraction, and classification.

pilot mental state detection machine learning EEG preprocessing

1. Introduction

The evolution of the aviation industry is heavily dependent on maintaining the highest standards of safety. Advances in aircraft design, endurance, and safety have led to a decrease in the number of aircraft accidents worldwide since the 1960s [1]. However, operator reliability remains a crucial factor in maintaining flight safety, as flight crews are responsible for a wide range of tasks, including receiving instructions from air traffic control, interpreting onboard instrument data, making course corrections, briefing cabin crew and passengers, and responding to unexpected events. Operating an airplane requires a high level of mental acuity, and these responsibilities can compromise flight safety [2][3][4]. According to data analyzed by the International Air Transport Association (IATA), there were 45 plane crashes caused by pilots losing control of the aircraft, resulting in 1645 fatalities between 2012 and 2021 [5][6]. Furthermore, the Commercial Aviation Safety Team (CAST) investigated 18 aircraft accidents in which pilots lost control and found that deficiencies in flight crew attention were involved in 16 of the 18 incidents [7]. As a result, CAST recommended that the aviation community, which includes government, business, and academic institutions, conduct research to detect and assess attention-related pilot performance deficiencies (APPD), specifically focusing on channelized attention (CA), diverted attention (DA), and startle/surprise (SS) mental states. CA is a state where pilots engage in a puzzle-based video game called Tetris while remaining focused entirely on the game without paying attention to other tasks. DA is a state in which pilots solve math problems that periodically appear while performing display monitoring tasks. Pilots who are in the SS mental state experience unexpected inversions of the primary flight display in the simulator.

To achieve this goal, researchers from both academia and industry have investigated a variety of approaches based on physiological signals and machine learning (ML) methods. In terms of physiological signals, quantitative sensors, both singular and multiple, have been employed to capture biological signals from the human body in both field studies and near-realistic laboratory environments. The electroencephalography (EEG) sensor is widely regarded as the most crucial physiological signal for analyzing mental states due to its ability to detect transient alterations in brain activity that may be indicative of pilots' attention deficits. It seems to provide the most accurate data for distinguishing mental states. It is also preferable to other methods of brain monitoring since it is safe, adaptable, non-invasive, and an utterly passive recording technique. Despite its advantages, EEG is notorious for picking up artefacts from environmental factors and physiological phenomena, such as muscle activity, ocular movements, line noise, and heartbeats, which compromise the quality of the signals. Therefore, isolating the neural signal relative to the cognitive processes that reflect brain activity from the recorded artefacts is crucial.

The presence of artefacts in EEG data can negatively impact the performance of ML models used to detect different mental states of pilots. To address this issue, researchers have employed various signal processing and feature extraction techniques. One approach is to record and combine EEG with non-brain physiological signals, such as functional near-infrared spectroscopy, electrocardiogram (ECG), galvanic skin response (GSR), and respiration (RP), simultaneously. However, the fusion of features derived from EEG and non-brain physiological signals may not always improve the performance of ML models [8][9]. Another approach is to utilize traditional preprocessing techniques to handle contaminated EEG data. Visual inspection and rejection, filtering, and Independent Component Analysis (ICA) are examples of such conventional denoising procedures. These methods, while effective, have several downsides, including the need for manual implementation, being slow and inefficient for longer recording sessions, and being difficult for beginners to execute [10][11]. These drawbacks highlight the importance of developing an automated preprocessing method.

Features or essential information embedded in the EEG signal are usually extracted after preprocessing, as they are crucial for classification tasks [12][13][14]. Both temporal and spatial features can be extracted from the EEG signals. For pilot mental state classification, temporal features in the time, frequency, and time–frequency domains are commonly extracted [15]. One such method that originates in the frequency domain is the power spectrum density (PSD). The presence or absence of shifts in the power spectra of individual EEG bands is an important indication of different mental states. In brain–computer interface (BCI) applications, spatial features are commonly extracted. They represent the active area of the brain. For pilot mental state classification, they are rarely used as input.

2. Multimodal Approach for Pilot Mental State Detection

The process of identifying mental states typically involves four steps: collecting data, cleaning it, selecting relevant features, and making predictions. The first step involves capturing signals from the brain and converting them into digital form. Then, to ensure accurate analysis, any extraneous noise or artifacts present in the data are removed through preprocessing. Next, specific characteristics of the data are selected and extracted in preparation for classification. These extracted features are then used by a classifier to make predictions about which class the data belongs to. As this process specifically relates to EEG data, the following provides a summary of previous research on the three stages of mental state detection: preprocessing, feature extraction, and classification.

2.1. Signals Preprocessing

An assortment of neuronal activity, physiological artefacts, and non-physiological noise can be found in raw EEG data. As their presence may hinder the performance of ML models [16], identifying and removing artefacts is a crucial preprocessing step before their use [17]. Although most research preprocessed their EEG data, there were a few exceptions [18][19][20]. To increase the signal-to-noise ratio (SNR), it is necessary to undertake a preprocessing procedure to eliminate extraneous noise and artefacts.

For the pilot's mental states classification, conventional preprocessing techniques, including filtering [16][21][22][23][24][25][26][27] and ICA [24][25][28], were employed on the EEG recordings. For example, Roza et al. [16] used a band-pass filter with a center frequency of 12–30 Hz to isolate the beta rhythm. Han et al. [25] used band-pass filtering at 0.1–50 Hz to remove the high frequency prior to removing eyes-related artefacts using the ICA algorithm. Similarly, Alreshidi et al. [29] used previously released pilot EEG data to analyze the influence of three preprocessing procedures on the efficiency of two ML models. The results demonstrated no discernible changes in the performance accuracies of the models when the data were filtered or when ICA was applied for eye-related artefact detection after data filtration. It has been established in the literature that typical preprocessing procedures for EEG data analysis necessitate knowledge and experience on the part of the analyst. Furthermore, they are only applicable when applied manually, requiring inspection, identification, and removal of faulty channels and contaminated data segments.

The past few years have seen the development of a number of partially or completely automated EEG preprocessing procedures that provide ways to clean EEG data. The Autoreject algorithm is an example of an automated preprocessing procedure that can be employed in EEG analysis pipelines [30]. It is a novel approach for automatically identifying and repairing erroneous segments in EEG data from single trials. It uses advanced statistical learning techniques, such as Bayesian hyperparameter optimization and cross-validation, to select amplitude thresholds to use for rejecting or repairing bad segments in EEG data. The Autoreject technique was used by Bonassi et al. [31] to automatically repair or reject contaminated epochs in EEG data. Pousson et al. [32] preprocessed the EEG data that were recorded from pianists doing musical tasks using the Autoreject method. There was a total of 10% erroneous epochs that were uncovered by the method and subsequently omitted from the investigation. Previous research has established that Autoreject has a significant role in the automatic purification of EEG data.

2.2. Feature Extraction

EEG is a set of stochastic signals that conceals extremely intricate data. Because of its high nonlinearity, its features are prone to sudden fluctuations. Human mental states, however, transition gradually from one state to the next [33]. Feature extraction aims to extract relevant features from data to map EEG segments to mental states.

Various features, such as statistical [16][22][34] and power spectral density features [16][18][21][22][23][24][25][28][34][35], have been extracted from pilots' EEG recordings in earlier research in order to classify pilots' mental states. For example, Wu et al. [28] used the power spectrum curve area representation of the decomposed delta, theta, alpha, and beta brain waves obtained using wavelet packet transform as features to perform the classification. Roza et al. [16] derived 15 distinct features from EEG and other physiological signals. The wavelet coefficients and several statistical features were extracted from the EEG signals. Furthermore, Binias et al. [26] extracted logarithmic band-power features using common spatial pattern (CSP) spatial filtering, which is widely used in BCI applications, from pilots' EEG recordings.

There has been a recent uptick in the use of Riemannian geometry-based feature extraction and classification algorithms for BCIs. The first implementation of these techniques in BCI applications was published in [36]. The authors employed the Riemannian mean covariance matrix distance as a feature for classification purposes. Additionally, they showed how the covariance matrices can be represented as vectors in the tangent space of the Riemannian manifold. Majidov and Whangbo [37] computed the covariance matrices obtained by using CSP spatial filtering and mapped them onto the tangent space of the Riemannian manifold. Singh et al. [38] used the data from the EEG electrodes to create spatial filters that reduce the dimensionality prior to employing Riemannian distance as a pattern recognition metric for classification. In addition, classifiers based on Riemannian geometry were used by Appriou et al. [39] in the proposed BioPyC toolbox. One such classifier is the tangent space classifier.

2.3. Mental State Classification

After EEG signals have had their features extracted, they must be classified using either a binary or multiclass ML approach. Because of the increased efficiency with which neural data may be analyzed and the need to decode brain activity, ML, and particularly Deep Learning (DL), algorithms have found widespread use in the field of computational neuroscience. Supervised ML algorithms, for instance, must first be trained using example data. The model and its learnt properties are then used to make predictions about the class label of new data that have not yet been seen.

For the detection of various pilot mental states, previous studies implemented various ML [18][22][23][24][25][26][27][34][35][40][41] and DL [16][18][25][26][28][35][42][43] algorithms. For instance, Han et al. [25] proposed a detection system based on multimodal physiological signals and a multimodal deep learning (MDL) network, consisting of convolutional neural network (CNN) and long short-term memory (LSTM) algorithms, to detect pilot's mental states, namely distraction, workload, fatigue, and normal. Roza et al. [16] proposed an emotion recognition system based on multimodal physiological signals and artificial neural network (ANN). The system was developed to detect five emotional states, namely happy, sad, angry, surprised, and scared. To identify the various states of mental fatigue, Wu et al. [28] presented a deep contractive autoencoder network; up to 91.67 percent of cases of the fatigued mental status of pilots could be correctly identified. In a flight simulator experiment, Johnson et al. [23] investigated probe-independent methods for categorization of three layers of task-complexity. The investigation was carried out using six classification algorithms, namely naïve bayes, decision trees, quadratic discriminant analysis, linear discriminant analysis (LDA), k-nearest neighbors (KNN), and support vector machine (SVM). Dehais et al. [40]

devised a scenario in which twenty-two pilots using a six-dry-electrode EEG system performed a low-load and high-load traffic pattern, as well as a passive auditory oddball. Zhang and Wang [24] proposed a concatenated structure of deep recurrent and 3D CNN to learn spatial–spectral–temporal EEG features for cross-task mental workload assessment. The findings reveal that the proposed approach achieved an average accuracy of 88.9%. Distinguishing between stages of brain activity related to idle but concentrated anticipation of visual cues and reactions to them using LDA, KNN, SVM, RF, and ANN algorithms was the focus of the research of Binias et al. [26].

Detecting and assessing APPD was also addressed in previous studies. For example, Harrivel et al. [35] employed RF, extreme gradient boosting, and deep neural network classifiers to predict CA, DA, and low workload states. As a preliminary study, through the use of different sensing modalities in high-fidelity flight simulators, the authors classified three types of mental states. Harrivel et al. [34] employed RF, gradient boosting, and two SVM classifiers to identify CA and SS states in further studies. The authors stressed the need for addressing the data quality issues. Terwilliger et al. [20] aggregated three mental states classes, namely CA, DA, and SS, into one class called event. To distinguish the event class from the NE mental state class, the authors presented a convolutional autoencoder approach. In previous research, people examined the effects of two preprocessing procedures on SVM and ANN using EEG data from a pilot exposed to CA, DA, SS, and NE states [29]. Although the models demonstrated the viability of combining data from two scenarios, the curse of dimensionality prevented them from accurately predicting the DA and SS states.

In the field of aviation, several studies have been conducted to evaluate the efficacy of EEG data in predicting mental states of pilots. Some of these studies have employed a binary classification approach to detect different mental states, while others have utilized EEG data in combination with other physiological data to improve performance.

Another notable limitation of previous studies is the limited sample size, with many only incorporating EEG data from fewer than 10 participants. This raises questions regarding the generalizability of their results, as the findings may only be applicable to a small subset of the population. While incorporating additional signals can sometimes improve model performance, it can also introduce additional noise and complexity to the system, making it more challenging to interpret the results.

Additionally, some studies have not disclosed the necessary information to make their work easily reproducible, while others have failed to make their datasets publicly available. This makes it challenging for other researchers to verify or build upon their findings.

Furthermore, some studies have not performed proper preprocessing techniques on their EEG data, such as advanced filtering and artefact removal, potentially compromising the validity of their results. The noise can interfere with the extraction of meaningful features and patterns in the EEG signal, leading to a decrease in the accuracy and reliability of the resulting model. To minimize the impact of noise on the performance of ML techniques, it is important to preprocess the EEG signal and remove as much noise as possible before training the model.

Regarding extracting meaningful features for the machine learning models, researchers have hardly ventured beyond statistical and PSD features.

To the best of our knowledge, current research did not attempt to combine multiple approaches from different areas to predict the pilot's mental states, which makes this study the first of its kind in the aviation field. The innovative nature of this study lies in the development of a novel multimodal approach to detect and classify APPD states using cleaned EEG data. The EEG signals from 18 pilots were collected from a variety of conditions to form the heterogeneous EEG data. The approach involves the automatic preprocessing of the EEG signals, feature extraction and selection methodology based on Riemannian geometry analysis, and a novel APPD system that classifies the APPD states. The system addresses the issues of corrupted EEG data, imbalanced datasets, and the curse of dimensionality, and provides meaningful features from the EEG signals, making it a unique contribution to the field.

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