Advancements in Monitoring Physical Fatigue in Aviation: A Comprehensive Analysis of State-of-the-Art ECG Sensor Technologies

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Keywords: ECG Sensor, Physical Fatigue, Human Factors, Aviation Safety, Monitoring Technology.

Abstract: Physical fatigue in aviation poses a critical challenge to flight safety, as it is characterized by causing reduced performance and feelings of tiredness, which can be temporary or chronic in nature, necessitating effective detection methods. Nowadays, due to very promising advances in non-obtrusive sensing technologies, wearable electrocardiography (ECG) devices have become a reliable physiological instrument to analyze the heart's behavior, and ultimately physical fatigue levels. In this study, a literature review is conducted to explore how detection of physical fatigue can be tackled in the aviation context through current advances in ECG technologies, delving into commercial-off-the-shelf ECGs from conventional adhesive electrodes to innovative textile-integrated alternatives. Our approach also involves a comprehensive analysis of the most relevant metrics, such as SDNN (standard deviation of the N-N interval), SDSD (standard deviation of successive differences), RMSSD (root mean square of successive N-N interval differences), pNN50 (percentage of successive N-N intervals differing by more than 50 milliseconds) and CV (coefficient of variation), regarding physical fatigue prediction in the distinct scenario of airplane cockpits. This includes detailing the latest updates and versions, along with addressing open challenges in deploying these sensors effectively within the aviation context. Hence, the core focus is on the pivotal role of ECG sensors, the technical requirements and methodologies needed in identifying physical fatigue to increase flight safety during a mission. This paper contributes to providing insights into the effectiveness of ECG sensors, exploring their integration into the cockpit and addressing challenges of incorporating effective computing and health monitoring in military aviation settings.

1 INTRODUCTION

When experiencing physical fatigue, muscles and central nervous system weaken, impacting force, productivity, or performance (Gonzalez et al., 2017). Fatigue can manifest as annoyance and reduced capabilities, with effects ranging from transient to chronic.

Specifically physical fatigue is categorized as either active, resulting from intense activities causing muscle soreness, or passive, stemming from monotonous work leading to symptoms like forgetfulness, drowsiness, and difficulty focusing (Hooda et al., 2022).

Previous studies suggest that fatigue poses a significant safety risk in civil and military aviation. European aviation's fatigue risk management report (Booth & Holmes, 2023) reveals alarming data: 25% of pilots experienced five or more microsleeps, and 72.9% had inadequate sleep between assignments.

Co-funded by
the European Union

This publication was funded by the European Union under the Grant Agreement 101103592. Its contents are the sole responsibility of the EPIIC Consortium and do not necessarily reflect the views of the European Union.

Florea, A., Arghir, S., Chira, A., Sollars-Castellanos, A., Sipele-Siale, O. and Calvo-Córdoba, A.
Advancements in Monitoring Physical Fatigue in Aviation: A Comprehensive Analysis of State-of-the-Art ECG Sensor Technologies.
DOI: 10.5220/0012950000004562

In *Proceedings of the 2nd International Conference on Cognitive Aircraft Systems (ICCAS 2024)*, pages 35-42
ISBN: 978-989-758-724-5

Additionally, nearly one in five pilots extended flight duties twice or more using the Commander's Discretion in the past four weeks. These statistics emphasize the pressing need for European airlines to improve fatigue management to safeguard crew welfare and flight safety.

Studies reveal that 72% of military pilots flew while extremely drowsy, with 94% of USAF pilots and navigators reporting significant fatigue affecting their performance (Caldwell & Gilreath, 2002), (Miller & Melfi, 2007). Modern fighter aircraft cockpits impose considerable psychological and physical stress, particularly during taxing activities like combat or cruise, leading to heightened weariness among pilots. Research indicates increased fatigue in F-15 pilots during long-haul flights, amplifying psychological stress (Ohrui et al., 2008). These findings underscore the necessity of robust fatigue (physical and mental) management strategies to safeguard aviation mission safety and effectiveness. In light of the aforementioned considerations, the present research paper focuses on the possibility of determining the installation of physical fatigue by monitoring cardiac activity for future applications for military aviation.

2 STATE-OF-THE-ART

Diverse methodologies quantify physical fatigue, reflecting its complex manifestation and impact. From traditional to advanced methods, various techniques provide insights into the physiological effects induced by fatigue. Multimodal approaches, including exploring cerebral, cardiac, ocular, electrodermal, respiratory, motor, glucose, and thermal activities, are prevalent with wearable sensors. These methods comprehensively assess fatigue, capturing physiological responses to exertion and stress.

Physical fatigue assessment often entails cardiac activity monitoring with photoplethysmography (PPG) sensors (Lohani et al., 2019). While PPG sensors detect pulse wave peaks to determine heartbeats, they are less precise than ECG sensors, particularly in identifying the R peak. Irregularities in pulse waveform morphology, like changes in peak characteristics, signify compromised cardiovascular function and heightened physiological stress linked to physical fatigue. Electroencephalography (EEG) captures shifts in wakefulness to sleep, with delta and theta activities showing consistency during fatigue, while alpha and beta activities decrease during maximal muscular contraction (Ng & Raveendran, 2007). Additionally, electrodermal activity (EDA) serves as an indicator of physiological arousal and emotional states, detecting changes in skin resistance. Increased skin conductance, decreased skin conductance reactivity, and delayed skin conductance reactions are commonly associated with physical fatigue (Aeimpreeda et al., 2020). Electromyography (EMG) sensors measure electrical impulses from muscles, with EMG magnitude rising in the presence of physical fatigue. Errors may arise due to movement, electrode misplacement, and cross-talk from neighboring muscles (Sueaseenak et al., 2017). Respiratory monitoring using pulse oximeters or pressure sensors shows increased rates and volumes with fatigue (Daiana Da Costa et al., 2019). Lastly, facial behavior analysis, including eye tracking, reveals fatigue-related indicators such as blinking, pupil size, and saccadic movement. Metrics like PERCLOS and blink duration reflect fatigue levels (Ji et al., 2004). Increased blink frequency is another sign of tiredness. Saccadic velocity decrease has been suggested as a biomarker of aviator fatigue (Göker, 2018).

Electrocardiography stands as a cornerstone in the exploration of fatigue across various domains, offering profound insights into the intricate relationship between cardiac rhythm and the autonomic nervous system. ECG, which records the heart's electrical activity via repeated cycles, is the gold standard test for determining cardiac activity. Electrodes are applied to the skin to acquire the electrical signal, which is later plotted as voltage versus time. ECG measurements are performed to evaluate heart function by using specific electrode configurations, such as the typical bipolar limb leads (I, II, III), chest leads (VV1–VV6), and amplified unipolar limb leads (aaa LL, aaa FF, aaVVsRR) (Meek & Morris, 2002). Heart rate (HR), the instantaneous measure of heart electrical activity, equates to the mean beats per minute (bpm) derived directly from R-R intervals (Berntson et al., 1997). Heart rate variability (HRV) denotes the variation in durations between consecutive heartbeats (Lewis, 2005). Balanced sympathetic and parasympathetic activities are requisite for relaxed states. Parasympathetic processes induce increased HRV, signifying relaxation, while sympathetic nervous system (SNS) activity maintains readiness during stress, resulting in reduced HRV and a higher heart rate. HR analysis yields time, frequency, and nonlinear parameters.

Heart rate data can be obtained over longer time spans, up to 24 hours, or during shorter intervals, ranging from 1 to 5 minutes. Frequency levels as well as time domain values are significantly impacted by the recording duration (Shaffer & Ginsberg, 2017). The categories for the recording periods are ultra short term (less than 1-minute recordings), short term (around 1–5 minutes recordings), long term (24 hours or longer recordings) (Anna Persson, 2019).

The time domain analysis encompasses all techniques that rely on the time R-R interval, which is often referred to as the N-N (normal to normal) interval. Some of the time domain parameters based on R-R intervals are SDNN (standard deviation of the N-N interval), SDSD (standard deviation of successive differences), RMSSD (root mean square of successive N-N interval differences), pNN50 (percentage of successive N-N intervals differing by more than 50 milliseconds) and CV (coefficient of variation).

Frequency domain analysis of ECG signals involves assessing the Power Spectral Density (PSD) to delineate energy distribution across specific frequency bands within R-R intervals. These bands are the following: Low Frequency (LF): 0.04-0.15 Hz; High Frequency (HF): 0.15-0.40 Hz; Very Low Frequency (VLF): 0.003-0.04 Hz; Ultra Low Frequency (ULF): <0.003 Hz (McCraty & Shaffer, 2015). The LF, HF, VLF, and ULF bands can represent activity in the autonomic nervous system and are associated with a number of physiological events (McCraty & Shaffer, 2015) . These bands are used to compute metrics such as ULF power, VLF power, LF peak, LF power, HF peak, and HF power, which offer insights into autonomic balance (McCraty & Shaffer, 2015) . The LF/HF ratio serves as an indicator of sympathetic and parasympathetic balance, although its consistency as a fatigue indicator across studies varies due to experimental differences and external factors (Hu & Lodewijks, 2020).

When a straight line cannot be drawn to represent the relationship between the variables, non-linear parameters are employed. They measure a time series' unpredictable nature, which represents the complexity of the mechanisms controlling heart rate variability (Shaffer et al., 2020). Commonly used parameters are SD1, SD2, SD1/SD2, approximate entropy, Shannon entropy, sample entropy.

After analyzing the time domain, frequency domain, and non-linear metrics, it is clear due to the fact that the flight scenarios are shorter, all measures based on 24-hour recordings have to be rejected. Metrics that can be obtained in 5 minutes or less, specifically SDNN, pNN50, RMSSD, and HR Max – HR Min, are desirable in a real-time processing situation. The HRV features can be found in Table 1.

Various categories of Commercial off the shelf (COTS) ECG sensors are available, catering to different needs and preferences. Wearable chest-based devices, such as the Zephyr BioHarness and Equivital Ex eq02, offer continuous monitoring of ECG signals and other physiological parameters, suitable for various activities. Compact patch devices like the VitalPatch Biosensor and Savvy provide lightweight and portable solutions for long-term monitoring, with discreet adherence to the skin. Integrated garment systems like the Master Caution System 2.0 offer comprehensive monitoring of multiple parameters, ideal for clinical or research settings. Traditional Holter monitors remain essential in diagnostic settings, providing high-resolution ECG

Table 1: HRV features.

Measures	Feature	Unit	Description
Time domain	meanNN	ms	Mean of NN interval sequence.
	meanHR	1/min	Mean of heart rate sequence.
	SDNN	ms	Standard deviation of NN interval sequence.
	RMSSD	ms	Root means square of successive differences in NN interval sequence.
	pNN50	%	Percentage of NN50 in total intervals.
Frequency domain	aLF	ms2	Absolute power of LF band.
	aHF	ms2	Absolute power of HF band.
	LF / HF	-	Ratio of aLF / aHF.
	peakLF	Hz	Peak frequency for LF band.
	peakHF	Hz	Peak frequency for HF band.
Nonlinear domain	SD1	ms	Standard deviations along the major axis of the ellipse.
	SD2	ms	Standard deviations along the minor axis of the ellipse.
	SD1 / SD2	-	Ratio of SD1 to SD2.
	Approximate entropy	-	Measures the predictability of a time series by quantifying the likelihood that similar patterns will continue in the data
	Sample Entropy	-	Quantifies the complexity of a time series by measuring the likelihood that similar patterns of data points persist within the series

Table 2: ECG Device.

Device name	Integration wearable technology	Sampling frequency [Hz]	Data transmission protocol	Data format	Battery
ZephyrTM Performance System	Shirt, chest strap, holder (direct)	1000 Hz	Bluetooth ECHO radio	.csv DaDISP .zsf	Lithium 3-hour charging cycle, up to 300 times.
Bittium Faros	Wearable Patch	1000 Hz	Bluetooth USB	EDF	7 days battery
BITalino	Patch	1000 Hz	Bluetooth	.csv	Li-Po battery, 8 hours
Equivital Ex eq02	Safe belt with dual shoulder straps	256 Hz	Bluetooth	.csv Excel raw	48h battery duration
VitalPatch	Patch	125 Hz	Bluetooth Radiofrequency	-	120-168h battery
Movesense developer kit	Chest strap	512 Hz configurable	Bluetooth	-	Coin cell
Savvy	Patch	125-500 Hz	Bluetooth	-	7 days battery
Master Caution System 2.0 by Healthwatch	Vest	200-1000 Hz	Bluetooth WiFi 3G, 4G USB	-	12h battery
Polar H10	Chest strap	1000 Hz	Bluetooth	-	400h, button shape.
MP160 Starter Systems with ECG100D (+ BioNomadix) by BIOPAC	Traditional ECG design (Einthoven triangle) Chest strap or shirt (using BioNomadix)	150 Hz	Ethernet Radiofrequency	.acq	Power supply 72-90h (using BioNomadix) 24h (Logger battery)

recordings over an extended period. Biopac Systems' modular data acquisition systems, including the MP160 Starter Systems with ECG100D amplifier, offer reliable and versatile solutions for research and clinical applications. Wireless transmission systems like BioNomadix provide flexibility and convenience for remote monitoring and data collection. The commercial products discussed in this section are summarized in Table 2.

3 MATERIALS AND METHODS

3.1 Sensor Technology

In order to acquire cardiac signals, the Zephyr BioHarness (Medtronic, Minneapolis, MN 55432-5604 USA) sensor and Biopac MP160 System (Biopac Systems, Inc., Goleta, CA 93117, USA) with an ECG100D amplifier were used (see Figure 1).

The Zephyr BioHarness is a wireless chest-based wearable device with multiparametric sensors for ECG, respiration, estimated core body temperature, accelerometry, time, and location. It offers three modes of wear: as a patch directly on the chest, secured within a chest strap, or integrated into a compression shirt. Weighing 18 grams and measuring 28 mm in diameter by 7 mm, it's designed for physical tasks. It records ECG at 1000 Hz, with a lithium battery lasting up to 300 recharge cycles. It can store data for 3.5 to 5 hours, communicates via Bluetooth Low Energy, and allows data backup in formats such as .csv, DaDISP, or .zsf files (Medtronic, 2018). The signal is recorded with the help of the OmniSense

Live software. After stopping the recording, the signal is automatically sent to the OmniSense Analysis software through which the heart rate can be seen in the form of a graph and the signal can be saved. Automated data processing enables direct extraction of heart rate information (Medtronic, 2017).

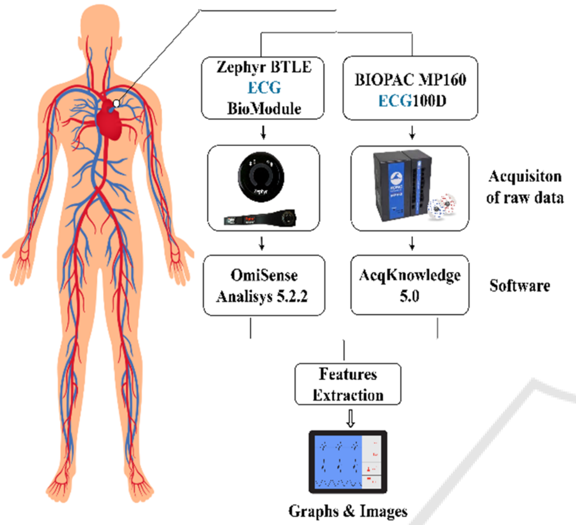

Figure 1: Block diagram.

The Biopac MP160 System with ECG100D Amplifier provides 16 channels for recording at sampling rates up to 200 KHz, ensuring comprehensive signal capture with a bandwidth of 0.05 Hz to 150 Hz. Weighing 1.154 kg and measuring 10 x 11 x 19 cm, it's powered via cable and connects through Ethernet for data transmission. AcqKnowledge software is used for the acquisition, visualization and subsequent saving of the signals. While not as wearable-friendly due to its size, its extensive capabilities make it suitable for detailed physiological studies. In contrast to the Zephyr system, the Biopac allows direct access to raw ECG signals for processing into measurements such as heart rate or heart rate variability (Biopac, 2019).

The Zephyr BioHarness offers distinct advantages over the Biopac MP160 system in terms of portability, ease of use, and real-time monitoring capabilities. Its lightweight and wearable design make it ideal for studies involving dynamic physical activities, whereas the Biopac system, while powerful, is better suited for stationary laboratory experiments.

Furthermore, the Zephyr BioHarness provides immediate access to physiological data via Bluetooth connectivity, enabling real-time analysis and intervention, whereas data acquisition with the Biopac system may require post-processing and offline analysis. As a result of these advantages, the Zephyr BioHarness will be utilized in future experiments to assess physical fatigue due to its suitability for real-time monitoring in dynamic settings.

3.2 Experimental Procedure

The test started with participants receiving and signing consent forms and GDPR documents, ensuring their informed consent and compliance with data protection regulations. A group of five male subjects, characterized by diverse demographics and physical fitness levels, participated in the study (age: 36± 12, height: 183 ± 7, weight: 93 ± 20).

The experiment consisted of two sequential phases: initially, participants underwent a rested state (RS) assessment (approximately 10 minutes) before commencing the actual workout, in order to obtain the individual's basal state of reference. During the initial phase, participants were equipped with a Zephyr ECG sensor positioned at chest level.

Subsequently, participants engaged in treadmill exercises (approximately 20 minutes) designed to induce physical fatigue (Figure 2).

Throughout the experiment, treadmill parameters were systematically adjusted to escalate both incline and speed, simulating strenuous physical activity. The Zephyr ECG sensor continuously monitored participants' cardiac activity during both phases, providing real-time data on heart rate and related metrics. This systematic data collection approach enabled the analysis of physiological responses to induced fatigue, with subsequent comparisons between the rested and physically-fatigued states (PFS).

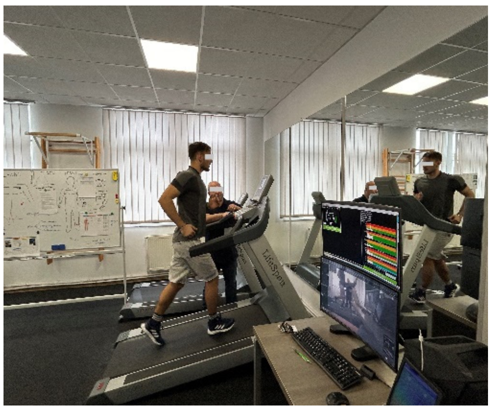

Figure 2: Demo session - Treadmill exercises.

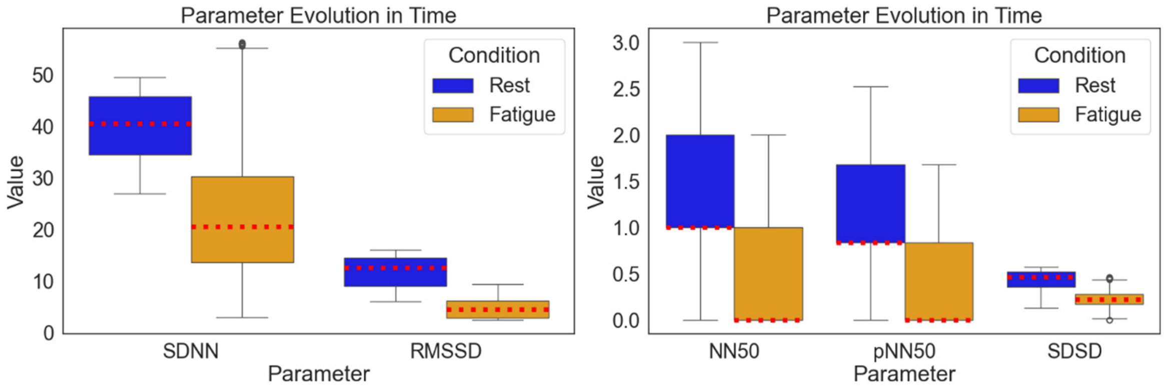

Figure 3: Parameters' distribution over time for rested and fatigue states.

4 RESULTS

The Zephyr ECG sensor was selected for these experiments due to its versatility, accuracy, and real-time monitoring capabilities. Overall, the Zephyr ECG sensor offered the necessary features and functionality to effectively capture and analyze participants' physiological responses to induced fatigue, making it the preferred choice for this study.

The RR interval is a time-domain indicator of the combined influence of the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS). Therefore, this paper focuses on the evaluation of parameters in the time domain in order to observe changes with the onset of physical fatigue. Time domain analysis is convenient when dealing with real-time requirements (e.g., short duration recordings). The recordings were taken during the rest period and then at the beginning of the physical exercise and until its completion. As mentioned earlier, we chose to work with 5-minute windows. Hence, we calculated the main indices: SDNN, RMSSD, SDSD, NN50 and pNN50. The distribution of the values obtained during the rest period and the running period on the treadmill are shown in Figure 3.

There are no generally acknowledged standard values for HRV indices that can be used for clinical purposes due to the variability from person to person influenced by age, sex, physical condition, etc. Despite this, we can still identify whether physical fatigue has been installed. That is because when physical fatigue sets in, the parasympathetic activity reduces, resulting in lower values for all the parameters (Shaffer & Ginsberg, 2017). This is also seen in the way the parameters are distributed in Figure 3. We can assume that because of the fatigue state, there are no considerable changes that occur in the durations of successive RR intervals. This is reflected in the low values of the median for NN50 and pNN50 parameters.

Additionally, we are able to state that HR levels are rising, indicating the effort expended during physical exercise. This occurs as a result of SNS activity (fight or flight), which is dominant under these circumstances.

5 DISCUSSION

Testing of the Zephyr and Biopac systems highlighted Zephyr's advantage in real-time monitoring during physical activity demonstrations, thanks to its wireless design and Bluetooth connectivity that allows immediate access to data. However, for cockpit integration, both devices can provide valid data but given considerations of space constraints and interaction with the pilot's equipment the Zephyr still manages to be a better fit.

Among the challenges encountered during the experiments were limitations on the viability of certain metrics due to their dependence on longer recordings, as well as the need to derive metrics only from the RR range. Some of the most widely used measures are SDNN, SDSD, and RMSSD, according to the literature (McCraty & Shaffer, 2015). This is appropriate for our research goal, but there are certain drawbacks. For example, we need to determine whether these short-term metrics accurately capture the physiological process we are studying and whether they yield more accurate results than 24-hour recordings, which could provide even more accurate data.

It was decided to choose only male subjects based on the dominance of this gender among pilots. Thus, the results are gender specific. A challenge encountered was the need to modify the training scenarios based on individual physical condition.

6 CONCLUSIONS

The selection of the Zephyr ECG sensor for these experiments was driven by its exceptional suitability for assessing physical fatigue. With its robust capabilities in real-time monitoring and accurate measurement of cardiac activity, including heart rate and related metrics, the Zephyr emerged as the optimal choice for capturing physiological responses during treadmill exercises. Its wireless design and comfortable chest-level positioning ensured seamless integration into the experimental setup, allowing participants to engage in physical activity freely. While acknowledging the versatility of the Biopac system for other types of data acquisition, the Zephyr's physiological responses solidified its position as the better option for this study.

Before and after fatigue, ECG data were examined using linear (time domain) dynamics. The findings indicated that following fatigue, the time-domain indices (SDNN, RMSSD, SDSD, NN50, and pNN50) decreased. The outcome confirms that assessing physical fatigue levels with HRV is a feasible approach (Shaffer & Ginsberg, 2017).

Examining pilots' physical fatigue is important for aviation safety. Pilots face demanding schedules and high-altitude environments, leading to fatigue. This can impair cognitive function and decision-making during flights. By understanding fatigue factors, interventions can be implemented to mitigate risks.

In future works, more sensors will be included, such as a photoplethysmograph, an electroencephalograph and an electromyograph. These sensors add to the real-time insights of physiological and cognitive changes during flight. Incorporating them enhances fatigue research, enabling targeted interventions and improving aviation safety standards. Future research will involve using flight simulators to induce fatigue through prolonged or intensive flight simulations.

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