Understanding Fatigue Through Biosignals: A Comprehensive Dataset

Marta Gabbi
258828@studenti.unimore.it
University of Modena and Reggio Emilia
Reggio Emilia, Italy

Luca Cornia
270012@studenti.unimore.it
University of Modena and Reggio Emilia
Reggio Emilia, Italy

Valeria Villani
valeria.villani@unimore.it
University of Modena and Reggio Emilia
Reggio Emilia, Italy

Lorenzo Sabattini
lorenzo.sabattini@unimore.it
University of Modena and Reggio Emilia
Reggio Emilia, Italy

ABSTRACT

Fatigue is a multifaceted construct, that represents an important part of human experience. The two main aspects of fatigue are the mental one and the physical one, that often intertwine, intensifying their collective impact on daily life and overall well-being. To soften this impact, understanding and quantifying fatigue is crucial. Physiological data play a pivotal role in the comprehension of fatigue, allowing a precious insight into the level and type of fatigue experienced. Though the analysis of these biosignals, researchers can determine whether the person is feeling mental fatigue, physical fatigue or a combination of both. This paper introduces MePhy, a comprehensive dataset containing various biosignals, gathered while inducing different fatigue conditions, in particular mental and physical fatigue. Among the biosignals closely associated with stress situations, we chose: eye activity, cardiac activity, electrodermal activity (EDA) and electromyography (EMG). Data were collected using different devices, including a camera, a chest strap and different sensors from the BITalino kit.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**.

KEYWORDS

Mental Fatigue, Physical Fatigue, Fatigue Comprehension, Biosignals, ECG, EDA, EMG, Eye Blinking

ACM Reference Format:
Marta Gabbi, Luca Cornia, Valeria Villani, and Lorenzo Sabattini. 2024. Understanding Fatigue Through Biosignals: A Comprehensive Dataset. In *Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction (HRI '24), March 11–14, 2024, Boulder, CO, USA.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3610977.3637485

HRI '24, March 11–14, 2024, Boulder, CO, USA

ACM ISBN 979-8-4007-0322-5/24/03.
https://doi.org/10.1145/3610977.3637485

1 STUDY OVERVIEW

1.1 Introduction

Fatigue is a multifaceted condition that extends beyond the mere physical tiredness. Despite numerous attempts by researchers to describe fatigue, it still lacks a unique definition, with many studies only capturing a small part of this broader and more complex concept [1]. Fatigue entails a wide range of physiological and psychological factors that can affect an individual's ability to function efficiently, leading to negative consequences on individual health and performance.

Due to its complexity, quantifying fatigue can be challenging. It can be measured through subjective measures, such as questionnaires, which are a simple way to gain insight into a person's emotional state. However, these measures are known to be subject to bias. On the other hand, physiological measures are unbiased and can be collected without interruptions, since the human body continuously produces physiological data [2]. Physiological signals, such as electromyography (EMG), electrocardiography (ECG), electrodermal activity (EDA), electroencephalography (EEG), eye-blink rates, can be analyzed to identify the physical and mental state of a human being.

Two main types of fatigue have been identified: mental fatigue and physical fatigue. The first one is experienced during and after demanding cognitive activities and is characterized by feelings of tiredness and lack of concentration [3]. The second one is induced by physical exercise, leading to a decrease in muscle power.

In this paper, we introduce MePhy, a dataset that includes physiological data collected while inducing mental and physical fatigue in the test participants. The signals were acquired in a non obtrusive way, using devices that did not limit subject's freedom to move. Hence, the approach used to collect data could be applied in real life scenarios, such an industrial working one. Given the numerous signals that can be obtained, we focused on four different ones: EMG, ECG, EDA, eye-blink rates, which are the most significant for fatigue detection [4–6].

1.2 Available Datasets

The goal of our experiment was to create a dataset that included various physiological signals collected while eliciting different types of fatigue. In previous works, mental and physical fatigue have been considered separately. The works presented in [9–12] are

Dataset	Participants	Biosignals	Type of Fatigue	Devices
WESAD [7]	15	ECG, EDA, EMG, BVP, RESP, TEMP, ACC	Rest, Mental	RespiBAN Professional, Empatica E4
PASS [2]	48	ECG, EEG, RESP, ACC, TEMP, GSR, PPG	Physical, Affective	BioHarness 3, Empatica E4, Muse S
FatigueSet [3]	12	ECG, EEG, EDA, PPG, TEMP, ACC, Gyroscope Data	Physical, Mental	Earable prototype, Empatica E4, Muse S, BioHarness 3
Stress recognition for automobile drivers [8]	17	ECG, EMG, GSR, RESP	Generic stress during driving tasks	Sensors, FlexComp analog-to-digital converter
MePhy	60	ECG, EDA, EMG, Eye Blinking	Rest, Mental, Physical, Combination of both	Polar H10, BITalino kit, Logitech C920

Table 1: Comparison among the available datasets considered.

focused on eliciting mental fatigue. In every one of these, mental strain was obtained by demanding cognitive activities, such as mental arithmetic tasks and robot movement control. In [13] and [14] the focus is on the effects of extended physical fatigue on physiological signals: in the first one, real industrial scenarios, like manual material handling and supply pick-up and insertion task, are simulated; the second one is based on aerobic exercises on a treadmill, a stationary bicycle and an elliptical trainer. In all of these studies, the only biosignal detected was the heart rate.

Although mental and physical fatigue have been considered as independent, there is evidence that they interact. It has been proved that mental fatigue emphasizes the perception of physical fatigue and, at the same time, cognitive functions can deteriorate after enduring physical challenges [15].

The work presented in [16] focuses on detecting the occurrence of both mental and physical fatigue, based on the assumption that individuals are exposed to several sources of fatigue simultaneously. Test participants endured a four-part experiment that aimed to elicit mental fatigue, physical fatigue and a combination of both.

The only physiological signal detected was the heart rate, collected with Polar H10, a chest strap.

This dataset builds upon the considerations from [16]. We included additional test subjects and new biosignals for analysis. Hence, the dataset provides a broader and more comprehensive view of biosignals and their correlation to stress and fatigue.

While reviewing different published works, we found a few datasets that best fit our study: WESAD [7], PASS [2], FatigueSet [3] and a dataset for stress recognition in automobile drivers [8]. Among all the datasets considered, there are no significant differences in terms of the collected biosignals, mainly ECG, EDA, EMG, but rather in the approach used to gather the data.

In particular, the WESAD dataset was focused on eliciting mental fatigue, not considering the physical component of fatigue.

The data available in the PASS dataset are achieved by inducing physical fatigue and affective fatigue, which is related to anxiety, discomfort or fear. The type of cognitive weariness that we induced during our experimental protocol is the mental fatigue, which refers to situations that require reflection and problem-solving abilities. Hence, the data collected mirror two different conditions.

The main focus of the data collection used for the FatigueSet dataset was investigating the effect of physical activity on the generation of mental fatigue. Hence, they only considered the physical aspect in correlation to the mental one.

Lastly, the dataset presented in [8] concentrates on collecting physiological data during real-life driving tasks to define a driver's respective stress level. In this work, they do not differentiate between a physical component and a mental one, since they considered three general level of stress (low, medium and high).

A brief and intuitive comparison among these datasets can be found in Table 1.

2 METHODS

The aim of our experiment was to create a diverse and comprehensive dataset to study fatigue and its correlation with biosignals. To achieve this, we conducted an experiment to collect physiological data through different wearable devices, eliciting both cognitive and physical fatigue. The experimental protocol adopted is depicted in Fig. 1.

In this section, we explain the conducted experiment.

2.1 Experimental Protocol

The experiment consisted of four parts and in each one the participant faced a different condition: rest, mental fatigue, physical fatigue, a combination of both. The total duration of the experiment was approximately of 25 minutes. Before starting the experiment, participants were asked to wear the chest strap and the sensors were applied. The test was then explained to the subjects.

The first phase, which lasted 3 minutes, was used to record the baseline activity of the participant. The subject was kept at rest and seated, without exposure to any stimulus.

The second phase was dedicated to stimulate mental fatigue, using the same test as in [12]. This test consisted in a combination of mathematics, memory and visual tasks that aimed to elicit cognitive effort and fatigue. An HTML-based application was developed and shown to the participants on a touch screen. We considered three

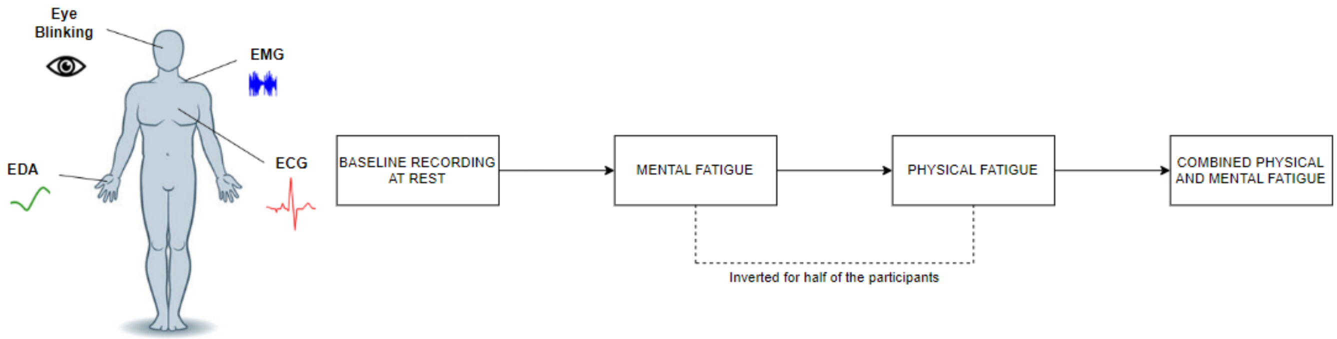


Figure 1: Organization of the experiment.

types of stressors, presented for 1 minute each. They are shown in Fig. 2a. These tasks were presented in random order and some were also repeated. The first task was the Stroop test [17] with five different colours and it was repeated twice. The next task consisted in math calculation of multiplications with operands from 1 to 13. This test was presented twice, but the second time with operands from 9 to 20. Then, the 2-back test [18] was introduced to participants, consisting in a sequence of different images shown to the subject, who had to identify whether the current image had appeared two images back in the sequence.

The physical fatigue was induced during the third phase of the experiment. The participants were asked to perform isometric exercises for biceps and triceps contraction, which consisted in holding a dumbell with different angles of elbow flexion. The angles we used were 0°, 45°, 90° and 135° and are shown in Fig. 2b. Every position was held for a minute and they were repeated twice. Each participant chose a weight that challenged them (2kg, 3kg or 5kg), allowing them to complete the entire phase without stopping. The order of these two phases was inverted for half of the participants, in order to compensate for the effect of one type of fatigue on the other.

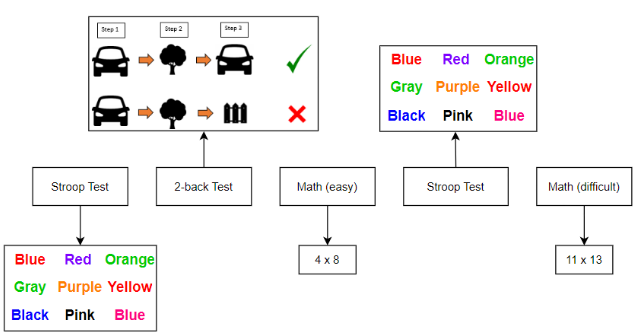
The last phase of the experiment aimed to induce mental and physical fatigue at the same time and, to do so, we combined the two tests mentioned before. Specifically, test subjects were asked to perform the mental fatigue induction test while holding a dumbell in a sitting position, as in the physical fatigue induction test. We noticed that it was necessary for the subject to have both hands free to perform the tests correctly and at the same time, in order to carry out the physical fatigue induction test with one hand and to keep the other one still for data collection. For this reason, the participant had to answer the cognitive tests by voice, in order to have them entered by the experimenter.

2.2 Experimental Setup

The chest strap Polar H10 was used to record cardiac activity and it was connected through Bluetooth to a laptop, accessing data using the GATT (Generic Attribute Profile) protocol. Data were acquired with a sampling rate of 1 Hz.

Eye activity was recorded using Logitech C920 camera, in order to capture the frequency of opening and closing of the eyelids. The sampling rate used was 30 Hz.

As regards EDA and EMG, the BITalino kit was used [19]. This kit includes: different sensors for biosignals acquisition, a microcontroller that converts analog signals in digital ones, and different types of cables. Data are acquired through a Bluetooth connection between BITalino sensors and a laptop and the software



(a) Mental fatigue inducing test. The test consisted in a combination of mathematics, memory and visual tasks executed following the sequence depicted in the figure.

(b) Physical fatigue inducing test. Each angle of elbow flexion was hold for 1 minute.

Figure 2: Organization of mental and physical fatigue inducing tests.

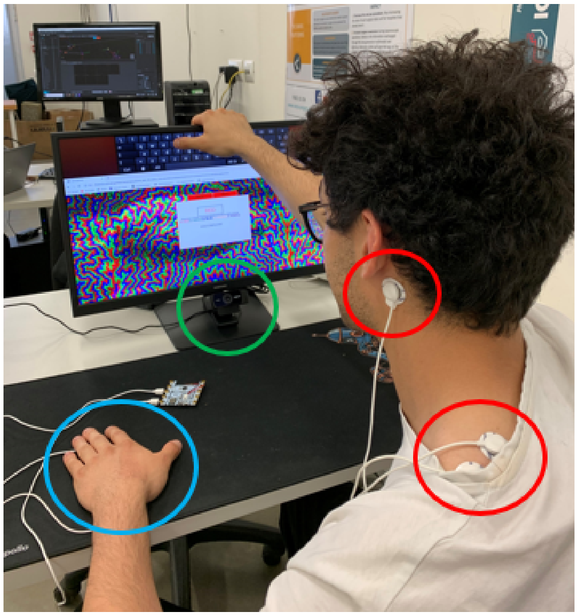


Figure 3: Placement of the sensors for EDA, EMG and eye blinking collection. The green circle highlights the position of the camera. The red circles indicate the region for obtaining EMG, while the blue circle the region for obtaining EDA. Polar H10 is not shown since it is worn under the shirt.

OpenSignals is required to be able to interface with BITalino. The data were sampled at a rate of 1000 Hz. The literature identifies the palm region of the hand for extracting EDA and the trapezius muscle region for obtaining EMG. Electrodes were thus applied to these two body areas on the opposite side from the dominant hand (e.g. electrodes are placed on the left side if the subject is right-handed).

The placement of the sensors and the camera is shown in Fig. 3.

2.3 Test Participants

60 subjects (30 females, 30 males, mean age: 22,85) were involved in the experiment. The candidates were volunteer students, who were completely new to the experimental tasks and goals of the experiment.

For the first half of the participants (30 subjects), we detected all of the biosignals presented in the paper; due to some issues encountered during signal acquisition, 11 recordings had to be removed, reducing the number of subjects with all four signals from 30 to 19. For the second half, the cardiac activity was the only biosignal collected. Nevertheless, the same experimental protocol was used in both cases.

Table 2 summarizes biosignals recorded for each subject.

The study protocol followed the Helsinki declaration and compliance to participate in the study was obtained from written informed consent before starting the experiment. All the data were reported anonymously.

	ECG	EDA	EMG	Eye Blinking
user0 to user18	✓	✓	✓	✓
user19 to user29	✓	✓	✓	X
user30 to user59	✓	X	X	X

Table 2: Biosignals recorded for each subject

3 DATASET

During the experiment, we collected four different biosignals from the participants: heart rate, EDA, EMG and eye blinking. We then organized the retrieved data in a main folder, one for each subject. Inside the candidate folder, there are additional subfolders where we find the breakdown into each physiological signal collected for that subject. Finally, each subfolder contains four text files in .txt format, each corresponding to a condition elicited during the experiment.

The MePhy dataset can be found at 10.5281/zenodo.8423405.

Data maintenance will be periodically carried out by the corresponding author.

4 ACKNOWLEDGEMENT

This work is supported by the "Lively Ageing" project, funded by the Italian Ministry of Health, the FAR Ricerca Diffusa 2023 "AURORA" project funded by the University of Modena and Reggio Emilia and the PRIN PNRR 2022 "ART.I.DE" project funded by the Italian Ministry of Education and Merit.

REFERENCES

[1] Ross O. Phillips. A review of definitions of fatigue – and a step towards a whole definition. *Transportation Research Part F: Traffic Psychology and Behaviour*, 29:48–56, 2015.
[2] M. Parent, I. Albuquerque, A. Tiwari, R. Cassani, J-F. Gagnon, D. Lafond, S. Tremblay, and T.H. Falk. Pass: A multimodal database of physical activity and stress for mobile passive body/brain-computer interface research. *Frontiers in Neuroscience*, 14, 2020.
[3] M. Kalanadhabhatta, C. Min, A. Montanari, and F. Kawsar. Fatigueset: A multimodal dataset for modeling mental fatigue and fatigability. *15th International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health)*, pages 204–217, 2021.
[4] G. Giannakakis, D. Grigoriadis, K. Giannakaki, O. Simantiraki, A. Roniotis, and M. Tsiknakis. Review on psychological stress detection using biosignals. *IEEE Transactions on Affective Computing*, 13:440–460, 2022.
[5] P. Schmidt, A. Reiss, R. Dürichen, and K. V. Laerhoven. Wearable-based affect recognition — a review. *Sensors*, 2019.
[6] U. Rajendra Acharya, K. Paul Joseph, N. Kannathal, C. M. Lim, and J. S. Suri. Heart rate variability: a review. *Med Biol Eng Comput*, 2006.
[7] P. Schmidt, A. Reiss, R. Dürichen, C. Marberger, and K. V. Laerhoven. Introducing wesad, a multimodal dataset for wearable stress and affect detection. In *Proceedings of the 20th ACM International Conference on Multimodal Interaction*, pages 400––408, 2018.
[8] J. A. Healey and R. W. Picard. Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions in Intelligent Transportation Systems*, 6:156–166, 2005.
[9] I. Hettiarachchi, S. Hanoun, D. Nahavandi, J. Iskander, M. Hossny, and S. Nahavandi. Towards more accessible physiological data for assessment of cognitive load - a validation study. *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 3045–3050, 2018.
[10] V. Villani, L. Sabattini, C. Secchi, and C. Fantuzzi. A framework for affect-based natural human-robot interaction. *27th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN*, 2018.
[11] V. Mishra, G. Pope, S. Lord, S. Lewia, B. Lowens, K. Caine, S. Sen, R. Halter, and D. Kotz. The case for a commodity hardware solution for stress detection. In

Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers - UbiComp '18, pages 1717–1728, 2018.

[12] V. Villani, M. Righi, L. Sabattini, and C. Secchi. Wearable devices for the assessment of cognitive effort for human–robot interaction. *IEEE Sensors Journal*, 20:13047–13056, 2020.

[13] Z. S. Maman, Y.-J. Chen, A. Baghdadi, S. Lombardo, L. A. Cavuoto, and F. M. Megahed. A data analytic framework for physical fatigue management using wearable sensors. *Expert Systems with Applications*, page 113405, 2020.

[14] S. Gillinov, M. Etiwy, R. Wang, G. Blackburn, D. Phelan, A. M. Gillinov, P. Houghtaling, H. Javadikasgari, and M. Y. Desai. Variable accuracy of wearable heart rate monitors during aerobic exercise. *Med Sci Sports Exerc*, 49:1697–1703, 2017.

[15] C. Zanoli, V. Villani, and M. Picone. The road to industry 5.0: The challenges of human fatigue modeling. *2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2023.

[16] V. Villani, M. Gabbi, and L. Sabattini. Promoting operator's wellbeing in industry 5.0: detecting mental and physical fatigue. *2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pages 2030–2036, 2022.

[17] J. R. Stroop. Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, pages 643–662, 1935.

[18] W. K. Kirchner. Age differences in short-term retention of rapidly changing information. *Journal of Experimental Psychology*, 1958.

[19] Hugo Plácido Da Silva, José Guerreiro, André Lourenço, Ana Fred, and Raúl Martins. Bitalino: A novel hardware framework for physiological computing. In *International Conference on Physiological Computing Systems*, volume 2, pages 246–253. SciTePress, 2014.