Use of EEG signals for mental workload assessment in human-robot collaboration

Andrea Ruo, Valeria Villani, and Lorenzo Sabattini

University of Modena and Reggio Emilia, Reggio Emilia RE 42122, ITALY
name.surname@unimore.it

Abstract. The present study aims to investigate the effect of human-robot collaboration on brain activity. To this end, we analyze differences in the electroencephalogram (EEG) power spectrum (Theta, Alpha and Beta frequency bands), and state-of-the-art indices, between some participants who performed different experiments, including a experiment of human-robot collaboration. In particular, tests included low cognitive load tasks, such as listening to classical music and watching a relaxing video; tasks with medium cognitive load through a collaborative robotics experiment, developed using the Niryo Ned robot, structured in three subtasks with increasing difficulty; and a high cognitive load task consisting of a sudoku game with tight time constraint. The EEG was recorded using the Neuroelectrics Enobio20 helmet. In addition to recording EEG signals, electrodermal activity (EDA) was recorded by means of a BITalino (R)Evolution Board in order to compare the results obtained from the two biosignals and evaluate the indices deriving from the spectral powers of the rhythms. Most of the workload indices, present in the literature, used for the analysis of this work have proved, on the basis of the analysis carried out, to be very good indices of the cognitive load.

Keywords: Human-robot collaboration; EEG power spectrum; EEG; EDA; Mental workload; Biosignals

1 Introduction

Mental workload (MWL) is defined as the amount of mental or cognitive resources needed to satisfy the current demands of a given task; it is also called psychological load and can be understood as the amount of brain activity in a unit of time, the occupancy rate of brain resources, the pressure or psychological information processing capacity of a person at work [1]. When perceived by a threatening stimulus, a cascade of physiological processes occurs that mobilize the body and the system to address the impending threat and ensure effective adaptation. Biosignals [2] that can be reliably measured in relation to such stressors include physiological (electroencephalogram (EEG), electrocardiogram (ECG), electrodermal activity (EDA), electromyogram (EMG)) and physical (respiratory rate, speech, skin temperature, pupil size, eye activity) measurements. A key goal in psychological and physiological research is to establish reliable biosignal indices that reveal the physiological mechanisms underlying the stress response. Studies have shown that an excessive mental workload can cause quickness, reduced flexibility, increase in errors and frustrated emotions and results in errors in the analysis of information acquisition and in decision-making [3]. Additionally, a too low mental workload can cause a waste of human resources and lead to a decline in job performance. Therefore, it is very important to analyze this disciplinary area in order to define human mental load states accurately.

MWL is traditionally assessed with questionnaires such as NASA Task Load Index (NASA-TLX) [4] or the Subjective Workload Assessment (SWAT) technique [5]. Since these methods only provide a subjective assessment of an operator's workload, the current trend is to supplement these assessments with physiological measurements using devices that measure bio-signals such as EEG. To properly evaluate MWL with such devices, it is necessary to be able to recognize the workload level of the input signal, and this can be achieved with the use of various machine learning techniques. About the EEG signals, with the development of technology, some studies have shown the effects of the Delta, Theta, Alpha and Gamma bands on mental workload [14]. It is generally believed that psychological stress, active thinking and attention cause EEG activity to shift to higher frequency bands and suppress Alpha wave activity [6]. Obviously, this topic offers many extremely interesting research areas, which include the analysis of a user's cognitive load, sleep disorders, epilepsy and brain-computer interfaces (BCI). Specifically, a BCI allows a subject to communicate and control the outside world without using the brain's normal activity through peripheral nerves and muscles. Messages are conveyed by spontaneous EEG activity or evoked by muscle contractions that are otherwise used for communication through speech and writing. People with severe neuromuscular disorders, or sometimes those completely paralyzed, benefit greatly from a BCI that offers them basic communication skills through which they can express themselves, for example, by checking a spelling program or operating a neuroprosthesis [7].

An equally important role in the analyzes is played by the analysis of EDA activity [8] that represents the measure of skin conductivity and is the physiological measurement of the flow of electricity through the skin. It is used to provide information regarding changes in the sympathetic nervous system, an indicator of cognitive fatigue and emotions. EDA recordings can be obtained using a bipolar montage from the palmar sites of the hand (such as two fingers) or from the feet where the highest density of sweat glands is observed.

The contribution of this paper lies in a study that compares two types of biosignals, EEG and EDA, with the aim of measuring the workload of participants during different types of tests, including a collaborative robotics experiment using the Nyrio Ned robot. The EEG signals were recorded using the Enobio20 helmet and were processed with an automatic algorithm that allows pre-processing operations (data removal, downsampling, rereference, filter application, bad channels removal) and application of independent component analysis (ICA) algorithm for artifact removal. In particular, to facilitate the identification of ocular artifacts, two Sticktrode electrodes were used for the acquisition of electroculographic (EOG) signals. EDA activity was recorded by means of a BITalino (R)Evolution using a bipolar montage from the palmar sites of the hand. In this way it is possible to evaluate the degree of accuracy of the indices found in the literature for the assessment of mental fatigue during human-robot collaboration tasks.

2 Materials and Methods

2.1 Partecipants

A total of three male university students (age $= 22 \pm 1$ years old) were analyzed. Participants gave written and informed consent to participate in the study. The only exclusion criterion from the following study relates to the fact that users were not to be subjected to diseases or drugs affecting the nervous system.

2.2 Experimental procedure

Before starting the study, participants were instructed on the procedures and protocol requirements during the different trials. All participants underwent a period of familiarization with the equipment required for the test as they had no experience with robots. The experimental room was calm and the light and temperature were continuously regulated. Participants conducted four different types of experiments: (A) listening to music, (B) watching a video, (C) performing human-robot collaborative assembly, and (D) solving sudoku game. In the first test, the user had to remain relaxed with his eyes closed listening to classical music with earphones, as shown in Fig. 1. In the second test, the user had to remain relaxed while watching a video on a computer. The third test, which consists of a collaborative robotics experiment, was organized in three tasks (C.1,C.2,C.3) of increasing difficulty. During these tests, the users had to assemble different figures by using "Duplo" bricks, supplied to them in a dedicated unloading box located inside the workstation through pick & place operations. Bricks were provided to the user in sequential or random order, depending on the task, by a robot, namely Niryo Ned robot [9], and a conveyor equipped with a proximity sensor. In particular: regarding C.1, the user has to assemble one figure, the blocks of which are passed to him in order of construction and can see the photo of the figure at any time. About C.2, the user has to assemble two figures, whose blocks are passed to him in order of construction and in random order, moreover he can see the photo of the figures once only. Regarding C.3, the user must assemble three figures, whose blocks are passed in order of construction and in random order and by means of a conveyor, moreover they can constantly see a drawing with different types of figures inside. The setup for this test is shown in Fig. 2. In particular, the six constructions shown in Fig. 3 were used during these tests, for a total of 44 pieces. In the fourth test, the user had to stay focused on playing a Sudoku puzzle of medium difficulty with a time limit.

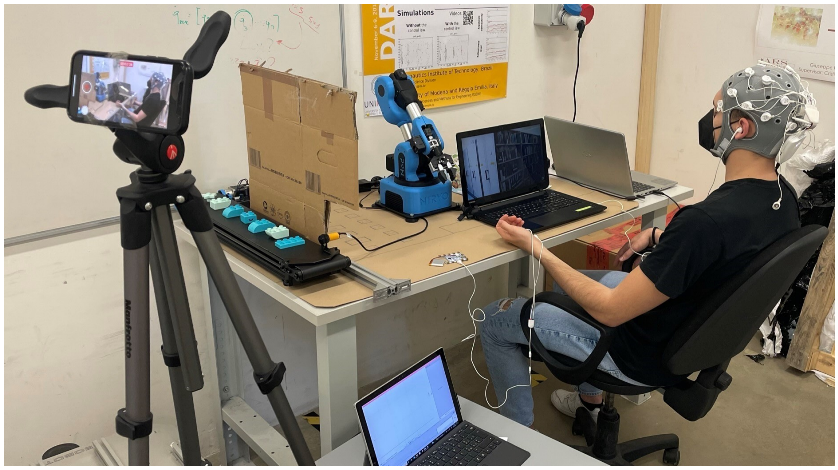

Fig. 1. Experiment setup when subjects were listening to music.

Between each experimental test (A, B, C, D) there was a pause of 3 minutes in order to prepare the experimental setup for the following test. This does not apply to the sub-tasks C.1, C.2, C.3 which have been carried out in sequence.

Considering successive improvements due to pilot testing, the enrolled participants performed the following tests: Subject 1 did A, C, D; Subject 2 executed A, B, C; Subject 3 performed C.

During all the tests the participants were subjected to the acquisition of the EDA activity. At the end of the experiment, the participants had to fill in a questionnaire to collect their personal evaluation regarding their state of relaxation and concentration during the various tests.

2.3 Instruments

The EEG data was evaluated using the Neuroelectrics Enobio20 device [10], a wireless electrode system, using a referential montage. The device is shown in the middle panel in Fig. 4. EEG was recorded from 19 scalp locations, according to the international 10-20 system: 17 EEG electrodes were Enobio NG Geltrode using electrode gel and 2 EOG electrodes were Enobio Stricktrodes. With reference to Fig. 5, the considered electrodes included frontal (Fz, F3, F4, F7, and F8), central (Cz, C3, and C4), temporal (T3, T4, T5, and T6), parietal (Pz, P3 and P4) and occipital (O1 and O2) locations, and two EOG electrodes (EOG1 and EOG2). Data were collected thorugh the software Neuroelectrics® Instrument Controller (NIC2) [11], which allows a computer to interact with Neuroelectrics devices. The electrodes placed in the mastoids served as a reference while recording on NIC2. A sampling rate of 500 Hz was used. The EEGLAB 2021.1 toolbox (MATLAB 2021.a) was used for preprocessing and data analysis. Raw data were filtered with a 50 Hz notch filter and a band pass filter with bandwidth 0.1–30

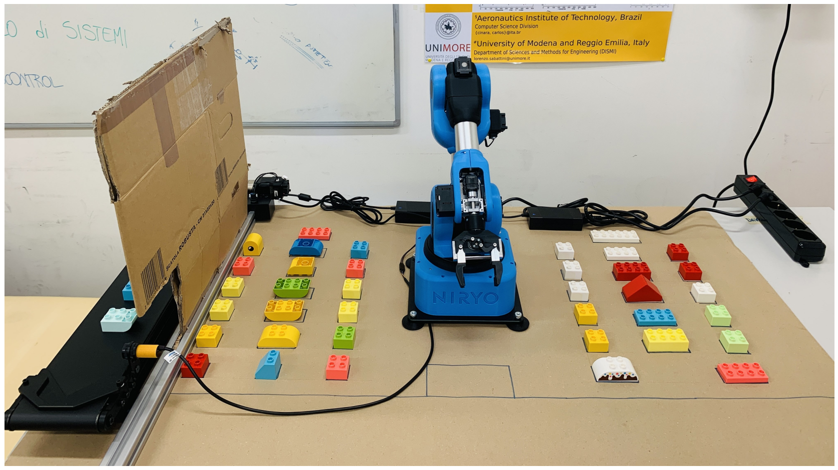

Fig. 2. Setup for the human-robot collaboration test.

Hz. Artifacts were corrected using independent component analysis (ICA). Spectral analyses were performed for the difficulty level of each test using MATLAB. The data were grouped into Theta (4–8 Hz), Alpha (8–12 Hz), and Beta (13–29 Hz) frequency bands.

As regards EDA recordings, we used BITalino (R)Evolution device, which is shown in Fig. 6. It is a kit of components for the detection of physiological data and is composed of a series of sensors designed to collect a large number of biological signals, from the measurement of muscle to heart activity, from small electrical signals coming from the skin to the detection of body movements. A microcontroller receives these analog signals and converts them into digital signals. EDA recordings were processed considering the approach in [13], using the software Weka [12].

Regarding the collaborative robotics experiment, the robot Niryo Ned, shown in Fig. 7, was used. It has the following characteristics: (a) Number of axis: 6; (b) Weight: 6.5 kg;(c) Payload: 300 g; (d) Max Reach: 440 mm; (e) Precision: 0.5 mm; (f) Communications: Ethernet 1 Gb/s, WIFI 2.4GHz & 5GHz - 802.11 g/g/n/ac, Bluetooth 5.0 BLE, USB.

2.4 Statistical Analysis

After carrying out ICA, the dataset was divided into epochs of 5 seconds, for a trade off between computational burden and reliability of results. In each epoch the spectral powers (µV/Hz) of the Alpha, Beta, Theta bands of the channels were calculated, considering the channels reported in Table 1. Moreover, we computed the state-of-the-art indices reported in Table 2 [14], [15], [16], [17]. In the literature it has been found that: i) Theta variation determines fatigue and mental workload; ii) Alpha variation decreases with arithmetic tasks and

Fig. 3. Figures to be assembled in the human-robot collaboration test.

increases with creative thinking; iii) Beta variation refers to visual attention and short-term memory; iv) BAT determines involvement in tasks and mental effort; v) TA refers to increased mental load; vi) TA ASS provides the same measurement of TA, with the difference that it is obtained from the ratio of two absolute measurements that are obtained from certain channels on the scalp.

Table 1. Spectral powers for the different frequency bands.

Rhythm Power	**Cortical Area**	**Channels**
Theta variation	Frontal e Temporal	F7, F3, F4, F8, Fz, T7, T8
Absolute theta variation	Frontal	Fz
Alpha variation	Parietal e Occipital	P7, P3, P4, P8, Pz, O1, O2
Absolute Alpha variation	Parietal	Pz
Beta variation	Frontal	F7, F3, F4, F8, Fz

3 Results

After data processing, plots of each recording were created for each subject. Figures 8, 9 and 10 show spectral powers and synthetic indices for Subject 1 in the different phases of the test (with reference to Subsec. 2.2, music, three collaborative tasks with the robot and Sudoku test).

Fig. 4. Enobio20 device.

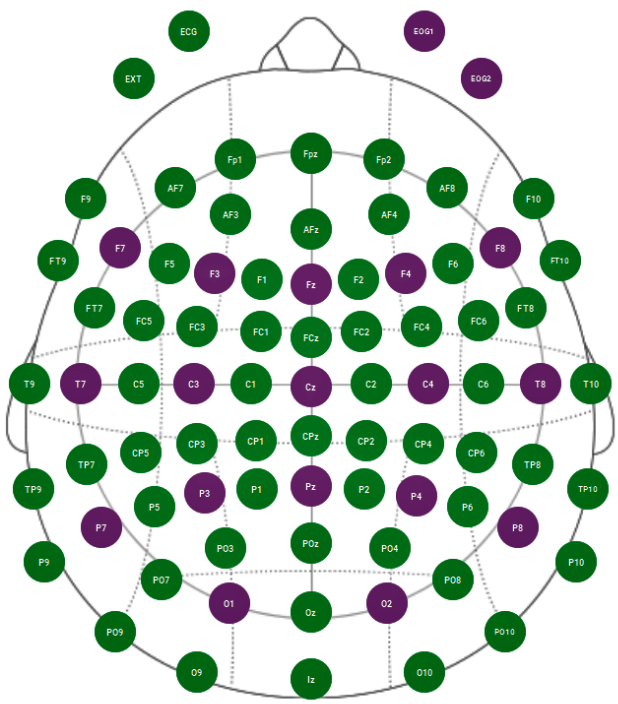

Fig. 5. Channel locations according to the international 10-20 system.

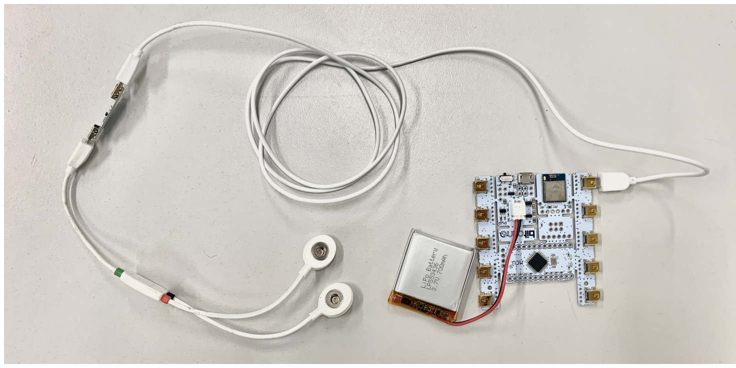

Fig. 6. BITalino (R)Evolution Kit.

Table 2. Indices for comparison among frequency bands.

Indices	**Definition**
BAT	$\frac{Beta}{(Alpha+Theta)}$
TA	$\frac{Theta}{Alpha}$
TA ASS	$\frac{ThetaAss}{AlphaAss}$

In addition, minimum, average and maximum values of each parameter of interest (see Tables 1 and 2) were computed. These are reported in Fig. 11.

Finally, as regards EDA activity, Fig. 12 plots recordings of Subject 1. It is noteworthy that an increase in the amplitude of the processed signal indicates an increase in stress and cognitive load on the user. Hence, Fig. 12 shows that Subject 1, according to the EDA activity, was more stressed during the tests at high workload (D, C.1, C.3) and less concentrated while listening to music (A).

4 Discussion

Comparing the results obtained from the comparison of the two biosignals with the replies to questionnaire, it was possible to carry out an analysis of the indicators present in the literature for the analysis of EEG signals. In particular, the green tag in Fig. 11 has been attributed to the very good indices and the yellow tag to the sufficiently good indices. With reference to Subsec. 2.4, it was found that: (a) MAX THETA represents a very very good index for mental fatigue assessment. It is present when there is mental fatigue and high concentration and cognitive load. (b) MAX ALPHA represents a very good index. It is present with high values when subjects had closed eyes, otherwise high values were found during creative thinking due to mental effort. (c) MAX BETA is a sufficiently good index. It is related to visual awareness and is present when there is an

Fig. 7. Niryo Ned robot.

increase in working memory. There were discrepancies in all participants with respect to the questionnaires. (d) MEAN THETA ASS is a very good index. It is related to the average concentration of the tests. (e) MEAN ALPHA ASS is a very good index. It is present with high values when subjects had closed eyes or during creative thinking due to mental effort. (f) MAX BAT is a sufficiently good index. It is related to mental effort. It has a discrepancy in Subject 2 as it should have a higher value in Task 2. (g) MAX TA is a very good index. It is related to the high cognitive load. (h) MIN TA is a very good index. It is related to low cognitive load. (i) MEAN TA ASS represents a sufficiently good index. It is related to the average stress during the tests, but did not prove reliable in our tests

On the basis of the considerations set out above, as regards Subject 1, it is possible to conclude that: (a) From the spectral power of the Theta rhythm, calculated in F7 - F3 - F4 - F8 - Fz - T7 - T8, it can be deduced that C.2 was by far the test that required the least mental effort; (b) From the spectral power of the Alpha rhythm, calculated in P7 - P3 - P4 - P8 - Pz - O1 - O2, it can be deduced that, during C.3 and D, an increase in creative thinking was found, probably due to to a mental effort; (c) The BAT index confirms a state of high concentration during D; (d) The TA index confirms a high workload during C.1, C.3, D and a reduced workload during A as the user is particularly relaxed. These results can be considered in agreement with those obtained from the analysis of the electrodermal activity, where C.1, C.3, D were found to be the experiments with greater amplitude value than the C.2, A.

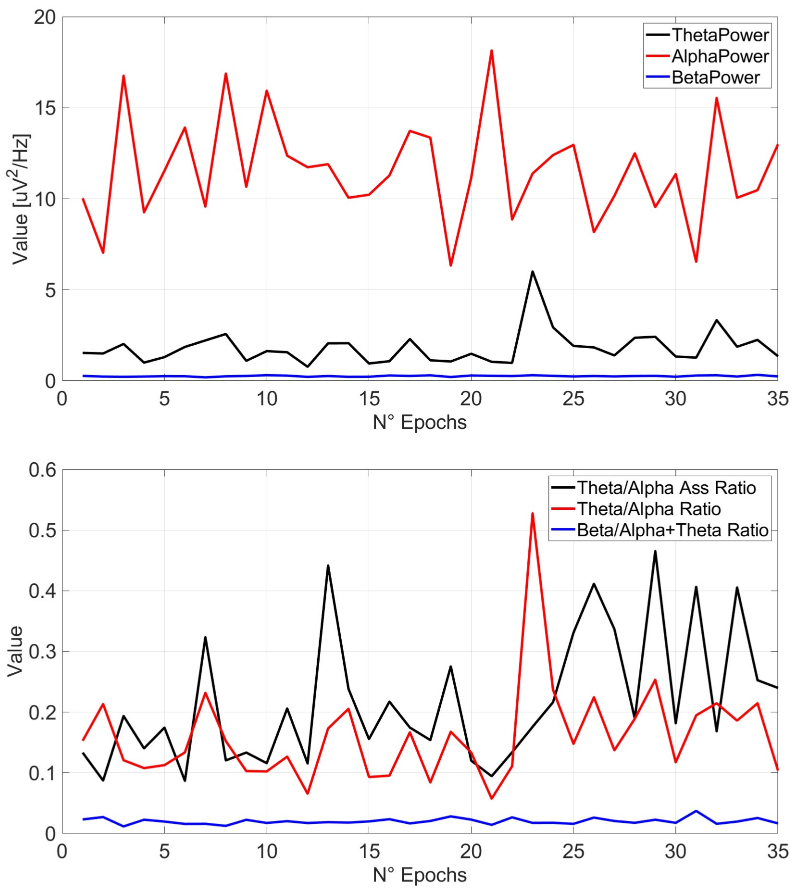

Fig. 8. Spectral powers and synthetic indices for Subject 1 while listening to relaxing music (A).

5 Conclusion

In conclusion, within this paper, two different types of biosignals, EEG signals and EDA activity, were analyzed by means of experiments designed specifically to cause different cognitive loads to the participants. In particular, a collaborative robotics experiment was developed to analyze in more detail the degree of stress and concentration on test subjects during engagement tasks with a robot. Recorded data were processed by means of EEGLAB for the EEG signals and Weka for the EDA activity and analyzed to in terms of spectral powers of the rhythms (Alpha, Beta, Theta) and the indices of workload present in the literature. Results have shown that spectral powers and state-of-the-art synthetic indices can be reliable indicators of workload during activities of everyday life and collaborative robotics experiments. In particular, in the participants, an in-

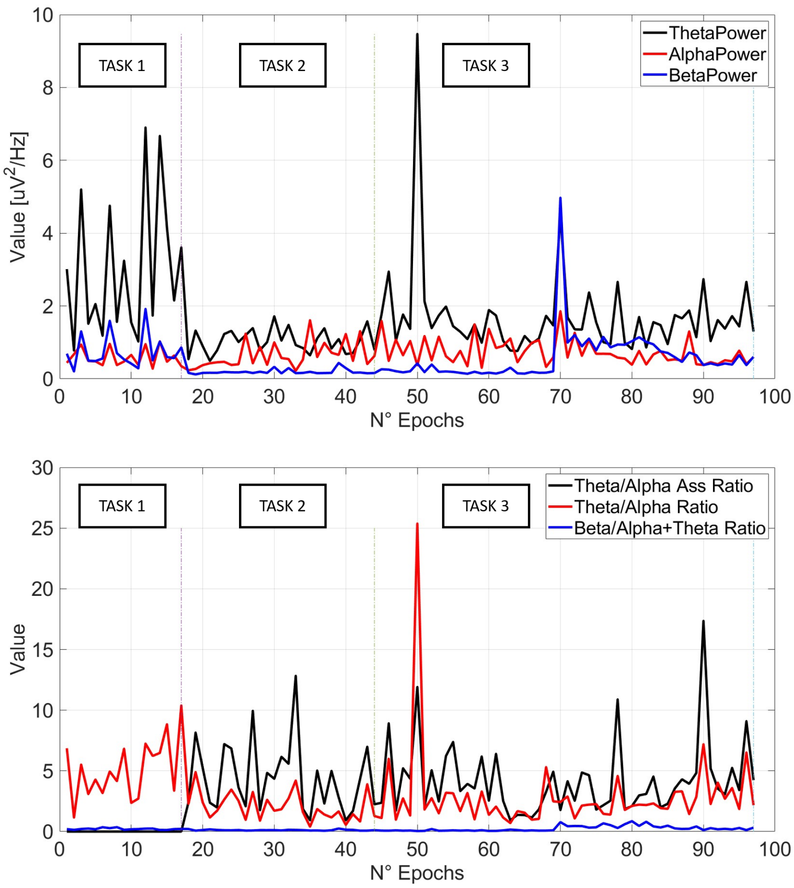

Fig. 9. Spectral powers and synthetic indices for Subject 1 while performing three tasks of human-robot collaboration (C).

crease in the Theta rhythm was found during the more complex tasks in the frontal and temporal area, and a greater creative thinking. Moreover, we found an increase in the Alpha rhythm in the parietal and occipital area during the more difficult tasks, likely caused by creative ideation and divergent thinking, as the subject was looking for alternative solutions.

6 Future works

This study represents a preliminary investigation and the achieved results need to be consolidated over a larger number of subjects. Additionally, a possible future development may be to measure cognitive load by calculating the average blink rate using EEGLAB's Blinker Tool. This tool allows the automated extraction

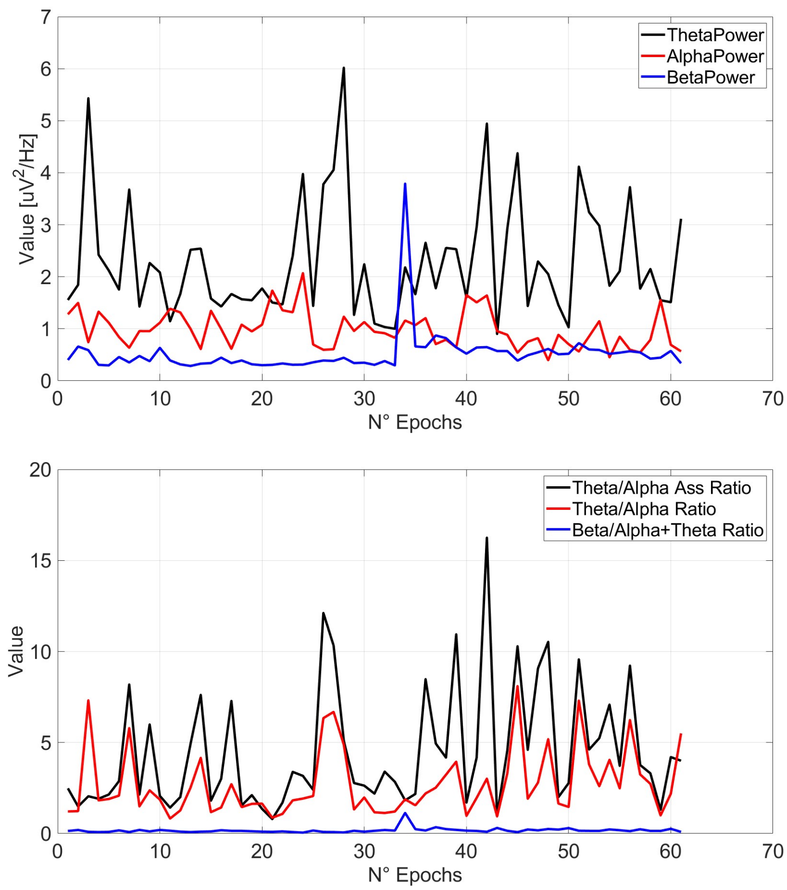

Fig. 10. Spectral powers and synthetic indices for Subject 1 while performing a Sudoku test (D).

of ocular indices from EEG, thus allowing large-scale [18] analysis. Therefore, it could be potentially interesting to analyze the users workload by means of another parameter deriving from the EOG signals. A second possibility of future development of this work may be to use the TPC/IP socket, made available by NIC2, to transmit data to any TCP/IP compatible application in real time.

Acknowledgement

The authors would like to thank Marianna Turrà for providing support in experiment design and analyzing EDA signals.

	Mental fatigue and workload			More creative thinking			High concentration				Medium task difficulty (ABSOLUTE)	
	THETA			ALPHA			BETA			THETA ASS		
SUBJECT 1	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN
TASK1	6.90	3.00	0.78	1.03	0.59	0.28	1.92	0.75	0.20	0.00	0.00	0.00
TASK2	1.71	1.03	0.49	1.61	0.65	0.22	0.44	0.19	0.12	4.06	1.94	0.67
TASK3	9.47	1.71	0.76	1.86	0.74	0.30	4.97	0.58	0.14	4.83	2.19	0.66
TASK123	9.47	1.75	0.49	1.86	0.69	0.22	4.97	0.50	0.12	4.83	1.74	0.00
MUSIC	6.01	1.81	0.77	18.15	11.56	6.33	0.33	0.26	0.19	4.66	2.09	0.80
SUDOKU	6.02	2.31	0.90	2.07	0.99	0.40	3.79	0.52	0.29	14.66	3.21	1.00
SUBJECT 2	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN
TASK1	1.8242	1.131	0.522	1.3884	0.7634	0.386	0.9196	0.4807	0.206	2.9883	1.3327	0.587
TASK2	2.6496	1.433	0.712	2.5318	1.1048	0.623	0.7421	0.3409	0.205	3.0356	1.7228	0.793
TASK3	1.4935	0.913	0.439	2.55	1.1647	0.564	1.3896	0.3797	0.191	2.4004	1.3759	0.612
TASK123	2.6496	1.1	0.439	2.55	1.0737	0.386	1.3896	0.3874	0.191	3.0356	1.466	0.587
MUSIC	1.9564	1.096	0.723	28.7	11.595	0.263	1.004	0.5157	0.171	3.2526	1.892	1.059
VIDEO	1.4855	0.871	0.592	2.0472	0.962	0.422	0.6258	0.3213	0.186	2.8322	1.3636	0.826
SUBJECT 3	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN
TASK1	3.2023	1.348	0.71	3.3934	1.0153	0.592	0.704	0.3957	0.296	2.4398	1.3092	0.556
TASK2	0.9663	0.665	0.439	1.8075	0.6709	0.427	0.2845	0.1792	0.113	1.5418	0.8522	0.406
TASK3	12.1753	1.176	0.596	6.6732	1.1503	0.516	0.6696	0.34	0.164	11.518	1.4691	0.477
TASK123	12.1753	1.075	0.439	6.6732	1.0117	0.427	0.704	0.3084	0.113	11.518	1.2928	0.406

(a)

		Medium creative thinking (ABSOLUTE)		Mental effort			Higher Workload		Lower Workload		Brain Beat: Stress	
	ALPHA ASS			BAT			TA			TA ASS		
SUBJECT 1	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN
TASK1	1.19	0.57	0.22	0.36	0.22	0.13	10.39	5.15	1.15	0.00	0.00	0.00
TASK2	1.66	0.57	0.13	0.25	0.12	0.07	4.90	2.05	0.40	12.83	4.43	0.93
TASK3	1.55	0.62	0.19	0.86	0.25	0.04	25.38	2.90	0.70	17.36	4.21	0.94
TASK123	1.66	0.60	0.13	0.86	0.21	0.04	25.38	3.06	0.40	17.36	3.53	0.00
MUSIC	24.07	10.87	4.34	0.04	0.02	0.01	0.53	0.16	0.06	0.47	0.22	0.09
SUDOKU	2.57	0.93	0.27	1.13	0.17	0.05	8.10	2.72	0.83	16.25	4.47	0.79
SUBJECT 2	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN
TASK1	1.3064	0.6118	0.288	0.415	0.256	0.142	2.5937	1.585	0.6013	4.617	2.4597	0.751
TASK2	1.7578	0.8921	0.347	0.247	0.136	0.077	2.1635	1.348	0.4177	6.5246	2.2677	0.703
TASK3	1.4037	0.6733	0.184	0.765	0.192	0.082	1.7298	0.869	0.3501	11.318	2.4055	0.9
TASK123	1.7578	0.7238	0.184	0.765	0.188	0.077	2.5937	1.137	0.3501	11.318	2.3766	0.703
MUSIC	23.866	8.6462	0.147	0.188	0.067	0.019	4.523	0.491	0.031	18.314	1.5754	0.075
VIDEO	2.2531	0.7548	0.409	0.298	0.183	0.094	1.9023	1.032	0.3595	4.667	2.1183	0.371
SUBJECT 3	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN	MAX	MEAN	MIN
TASK1	0.8507	0.4449	0.225	0.259	0.181	0.107	2.7498	1.438	0.8976	4.5749	3.1417	1.025
TASK2	0.936	0.4787	0.265	0.223	0.138	0.078	1.5557	1.059	0.4713	3.3055	1.9576	0.758
TASK3	2.6105	0.6165	0.192	0.33	0.169	0.017	2.0393	1.029	0.4857	8.4294	2.6829	0.664
TASK123	2.6105	0.5572	0.192	0.33	0.163	0.017	2.7498	1.097	0.4713	8.4294	2.5706	0.664

(b)

Fig. 11. Minimum, mean and maximum value of spectral powers and synthetic indices for each test participant, in each phase of the experimental procedure.

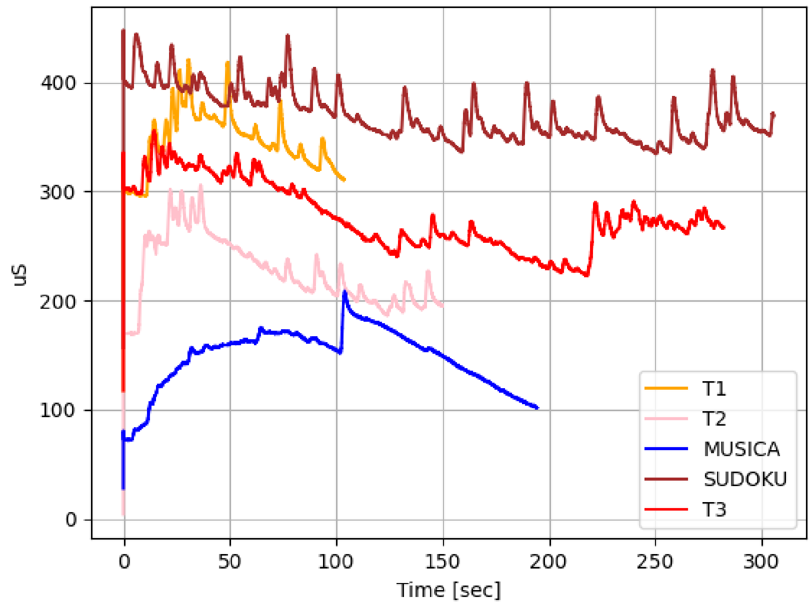

Fig. 12. EDA activity for Subject 1.

References

1. Hao, G.; Zhong, Y. MentalWorkload Assessment Based on EEG and A Hybrid Ensemble Classifier. Softw. Guide 2019, 18, 1–4
2. Giorgos Giannakakis Member, IEEE, Dimitris Grigoriadis, Katerina Giannakaki, Olympia Simantiraki, Alexandros Roniotis and Manolis Tsiknakis, Member, IEEE: Review on psychological stress detection using biosignals
3. Salomao, T.; Alberto, L. Operator Functional State Modelling and Adaptive Control of Automation in Human-Machine Systems. Ph.D. Thesis, University of Sheffield, Sheffield, UK, 2016
4. S. G. Hart and L. E. Staveland, "Development of NASA-TLX (task load index): Results of empirical and theoretical research," Adv. Psychol., vol. 52, pp. 139–183, Apr. 1988.
5. G. B. Reid and T. E. Nygren, "The subjective workload assessment technique: A scaling procedure for measuring mental workload," Adv. Psychol., vol. 52, pp. 185–218, Jan. 1988.
6. Li, Z.; Dong, Y.; Guo, X. Hybrid brain-computer interface system based on alpha wave and motor imagery. J. Electron. Meas. Instrum. 2014, 28, 625–629 https://link.springer.com/article/10.1557/jmr.2014.218
7. Leif Sornmo, Pablo Laguna: Bioelectrical signal processing in cardiac and neurological application
8. John Cacioppo; Louis G. Tassinary; Gary G. Berntson: The handbook of psychophysiology
9. Nyrio Ned https://niryo.com/product/ned-education-research-cobot/
10. Enobio 20 Neuroelectrics https://www.neuroelectrics.com/solutions/enobio/20

11. Neuroelectrics® Instrument Controller (NIC2) https://www.neuroelectrics.com/solution/software-integrations/nic2
12. Weka 3: Machine Learning Software in Java https://www.cs.waikato.ac.nz/ml/weka/
13. Raquel Martinez; Asier Salazar-Ramirez; Andoni Arruti; Eloy Irigoyen; Jose Ignacio Martin; Javier Muguerza: A Self-Paced Relaxation Response Detection System Based on Galvanic Skin Response Analysis. https://ieeexplore.ieee.org/document/8680625
14. Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments. https://www.frontiersin.org/articles/10.3389/fnins.2020.00040/full
15. Estimating Brain Load from the EEG. https://www.researchgate.net/publication/26681847_Estimating_Brain_Load_from_the_EEG
16. Int. J. Environ. Res. Public Health 2020 https://doi.org/10.3390/ijerph17010046
17. Bujar Raufi, Luca Longo: An Evaluation of the EEG alpha-to-theta and theta-to-alpha band Ratios as Indexes of Mental Workload https://www.researchgate.net/publication/358919573_An_Evaluation_of_the_EEG_alpha-to-theta_and_theta-to-alpha_band_Ratios_as_Indexes_of_Mental_Workload
18. Github Repository http://vislab.github.io/EEG-Blinks/