Evaluation of Gel and Dry Electrodes for EEG Measurement to Compare Their Suitability for Multimodal Workload Detection in Humans

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Abstract: In this paper we aim to investigate whether the use of dry electrodes to detect multimodal workload could be a viable way forward in the future. Therefore, we did a comparative study with gel (6 subjects) and dry electrodes (2 subjects) and analysed the data using the Task Load Index (TLI) and the power spectrum of different frequency bands. The results show that the TLI is significantly increasing for higher workload condition ($p < 0.04$) and expected changes in the frequency bands are significant for both gel and dry electrodes in subject-specific frequency bands. In conclusion, the results look promising, and it is worthwhile to conduct another study with more subjects using dry electrodes.

1 INTRODUCTION

To know the overall workload level of a person during a certain task is helpful in different areas. For the prevention of mental disorders as, for example, burnout due to permanent stress and overload, it is an advantage to know the overall workload level of a person (Greif & Bertino, 2022), as the tendency towards mental disorders increased in the past (World Health Organization, 2023) and this must be avoided as much as possible. Safety-critical environments in particular need to be better monitored in terms of workload to protect the people who work in them. In space flight, for example, it is important to know the workload level of each astronaut, since a higher level of workload is related to a higher risk to make mistakes (Morris & Leung, 2006) and this can quickly end fatally. Further, microgravity on ISS and in space (ESA, 2023) will likely have an impact on the overall workload since astronauts are not used to it in general. The Multiple Resource Model by Wickens (2008) defines different dimensions influencing workload. Objects that are in microgravity behave significantly differently than those in Earth gravity. As a result, visual processing and special activities consume more resources because the objects astronauts see behave differently than they would expect. Thus, investigation of the adaption of workload under different gravitational conditions is important.

The literature shows that workload can be determined based on different physiological signals (Fairclough & Mulder, 2011; Singh, Ponzoni Carvalho Chanel, & Roy, 2021; Volden, Alwis, de Viveka, & Fostervold, 2018; Ding, Cao, Duffy, Wang, & Thang, 2020).

Different modalities can be investigated to estimate workload under different gravitational conditions. The following modalities are of special interest for our future research:

- Electroencephalogram (EEG),
- Eye Tracking (ET),
- Electrocardiogram (ECG) and
- Respiration (RESP)

EEG and ET are very common parameters for workload estimation. ECG and RESP are very interesting for space applications, since different gravity conditions have an impact to the cardiovascular system of a person (Schlegel, et al., 1998) as well.

The aim of this paper is to see, if a measuring system with dry electrodes in form of a headset could

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be used for EEG measurement, since one big advantage of such a device is that every person could set this up on their own in a few seconds (Trampler, Tabie, Rotonda, Heere, & Kirchner, 2021) which would be required under conditions such as space exploration with few persons and time available. To test this, we conducted a study with both, a gel and dry electrode system. Subjects had to solve the same cognitive demanding tasks. To verify, which of the systems is better suited for our aim, we looked at the data measured during an N-back task (Kirchner W. K., 1958).

The remainder of the paper is structured as follows. In the next section, we provide an overview about the EEG parameters that change due to different workload conditions. In section 3, we introduce the experimental setup of the study and discuss the used methods. Afterwards, we explain the results of the EEG analysis and discuss them in section 5. In section 6 we give a conclusion about the outcome.

2 WORKLOAD DETECTION BASED ON THE ELECTROENCEPHALOGRAM

This section provides information about the EEG and the expected changes caused by “lower” and “higher” workload. “Lower” workload was evoked by a clearly simpler task with less demand on working memory.

The EEG measures brain activity with very high time resolution by measuring the potential difference between two electrodes (Berger, 1934). Some parameters in the EEG are reported in literature that change with different levels of workload.

For features in the time domain Pergher et al. (2018) reported a higher P300 amplitude for lower workload and the highest at the electrodes Fz, Pz and Cz. A reduced amplitude of the P3a in an N-back task was found as well (Putze, Mühl, Lotte, Fairclough, & Herff, 2018). Kirchner et al. (2016) showed a reduced P3b for high task load, i.e., workload caused by a task.

For features in the frequency domain a lot more literature can be found in context to N-back tasks and workload in general. Klimesch (1999) and Andreassi (1995) reported that theta and alpha oscillations are sensitive to task difficulty. Some groups reported a change in the alpha band power over parietal sites (Ding, Lu, Lin, & Tseng, 2016; Ewing, Fairclough, & Gilleade, 2016). Ding et al. (2016) reported in detail that they found a stronger alpha 1 (8-10 Hz) activity in insula but a weaker alpha 2 (10-12 Hz) activity in the anterior cingulate cortex for higher workload after source reconstruction, compared to lower workload. Ewing et al. (2016) calculated the frequency bands for every subject individually and reported a decrease in lower alpha band power (7.5-10 Hz) in the right hemisphere. For upper alpha band power (10.5-13 Hz) they reported a decreasing power with increasing demand.

The theta band power (4-8 Hz) was shown to change during an increase of workload, while the theta band power in the frontal sites does increase (Bagheri & Power, 2020; Ewing, Fairclough, & Gilleade, 2016; Shou & Ding, 2013). Nowak et al. (2021) showed that an increase in theta band power at frontal electrodes leads to better results in N-back tasks. Ding et al. (2020) reported this especially for the Fz electrode. Another group showed a stronger theta activity in temporal regions 335 ms after the stimulus onset (Ding, Lu, Lin, & Tseng, 2016).

Two groups showed an increase in beta band power (13-25 Hz) for higher workload compared to lower workload. Matthews et al. (2017) explained that they would interpret the higher beta band power as a direct expression of attentional overload or as an indirect product of cognitive self-regulation. Singh et al. (2021) found the higher beta band power mostly in the fronto-central, temporal and occipital sites.

Changes in gamma band (25-45 Hz) are also dependent on workload. Singh et al. (2021) showed an increase in gamma band power for higher workload, compared to lower workload in the brain areas in which changes in beta activity were found.

To define the level of workload of a person, it is also common to use the ratio of frequency band powers of certain electrodes. For example, the Task Load Index (TLI) is defined as the ratio between the averaged power of the theta band at Fz and the averaged power of the alpha band at Pz (Smith, Gevins, Brown, Karnik, & Du, 2001).

3 METHODS

This section contains information about the dataset in general, the experimental setup and procedure, the data recording and pre-processing and the EEG analysis.

3.1 Data

The data were recorded in two separated studies but with the same experimental setup. The data for dry electrodes and detailed information about the headset are already published (Trampler, Tabie, Rotonda, Heere, & Kirchner, 2021). These data were originally recorded to explore the fit of the headset with five subjects. The headset and its layout can be seen in Figure 1.

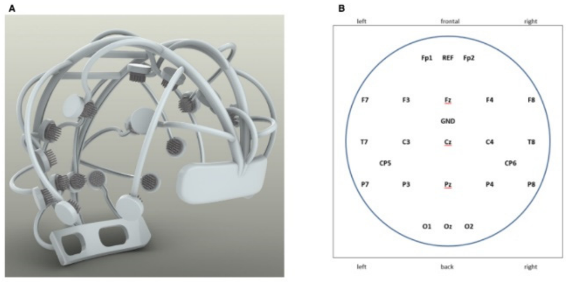

Figure 1: A: Dry electrode headset with integrated electrodes; B: layout (Trampler, Tabie, Rotonda, Heere, & Kirchner, 2021).

The data with gel electrodes were afterwards recorded with six subjects to compare dry electrodes with gel electrodes.

The particular challenges of dry electrode systems are both the signal quality and the wearing comfort for the subjects, especially during longer measurements. The electrodes must be placed on the skin with a certain amount of pressure in order to establish contact between the electrode and the scalp with the appropriate impedance and to ensure good signal quality. However, the pressure must not be too high, as the test subjects would otherwise suffer pain. This can be influenced by the flexibility of the headset. The number of pins per electrode also has a further influence on wearing comfort, as the pressure is distributed over a larger area with more electrodes and has no influence on the impedance (Fiedler, et al., 2018).

3.2 Participants

EEG and ET data from eight healthy subjects (6 male, average age = 29,8 ± 6,8) were included in this study. All subjects gave their written informed consent and were told that they could stop the experiment at any time without consequences. The studies were approved by the local Ethical Committee of the University of Bremen. Subjects received a monetary compensation of 10€ per hours.

3.3 Experimental Setting

Throughout the experiment, every subject executed three sets with four different tasks each, always in the same order. After every task the subject had to answer the NASA-TLX questionnaire (Hart & Staveland, 1988). There was a 60-seconds break between every task. After each set there was a break of five minutes. The difficulty of the tasks increased with each set. The experimental design can be seen in Figure 2.

The first task was a mental rotation task (Shephard & Metzler, 1971) where subjects had to decide which of the shown objects are the same but rotated.

The second task was a visual N-back task (Kirchner W. K., 1958). The easiest level was N=1, the middle level N=2 and the most difficult N=3. Square figures, as shown in Figure 2, were shown to the subjects. Subjects were instructed to press a button if the stimulus was a target. The number of targets were between 20 and 30 and the number of non-targets between 160 and 248 for every subject. This difference in the number of stimuli is due to the experimental design. Subjects had a time limit for the task and had to process as many stimuli as possible. The presentation time for each figure was 500 ms and the inter-stimulus interval 2000 ms.

The third task was an arithmetic task in which the subjects had to perform an addition or subtraction with two numbers. The time limit was ten seconds for each level of difficulty.

The last task was the Stroop test (Stroop, 1935). Here, the levels of difficulty were always the same as this task was a control task for workload conditions.

For the purpose of this paper only the EEG-data from the N-back task are important and used for evaluation.

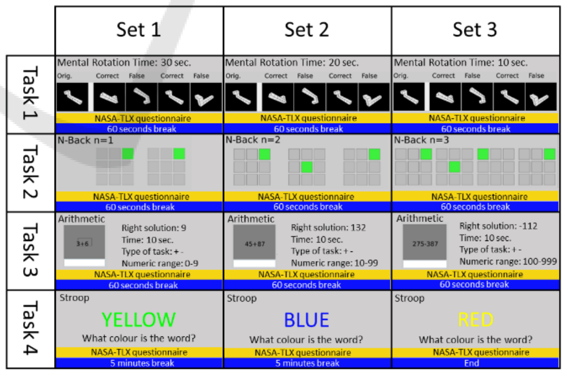

Figure 2: Experimental design.

3.4 EEG Recording and Pre-Processing

Before the experiment started, each subject was prepared with the Pupil Core Eye Tracker from Pupil Labs (https://pupil-labs.com/products/core/) with a sampling frequency of 200 Hz @ 192x192px and an accuracy of 0.60°.

Subjects were also prepared with the EEG system. ANT eego myLab (https://www.ant-neuro.com/products/eego-mylab) with a sampling rate of 500 Hz was used. Six of the subjects (WK76, RR09, JR48, AA70 VA13 & BS09) were prepared with 64-channel Ag/AgCl active gel electrodes, positioned according to the 10-20 system with reference at FCz. The other two subjects (FW00, SD50) were prepared with a 24-electrode tailor-developed headset with dry electrodes also according to the 10-20 system, where each electrode is positioned by an arch that adjusts its pressure to the appropriate force (for more detailed information see (Trampler, Tabie, Rotonda, Heere, & Kirchner, 2021)). The 24 electrodes used were defined as the optimal minimum before the headset was built. As explained in Trampler et al. (2021), three other subjects were measured with the dry electrode headset, but we were unable to record an EEG signal because the electrode cap did not fit properly. The dry electrode headset was tailor-developed to fit subject FW00 perfectly.

During the experiment, both EEG and ET were measured the entire time.

Pre-processing was done with the MNE python-library. The data were down-sampled to 256 Hz and a bandpass filter between 0.1 and 40 Hz was applied.

3.5 EEG Analysis

To analyse the EEG data, the N-back task data were segmented into epochs of 15 seconds without any overlap and without consideration of the target- / non-target-events. Power Spectral Density (PSD) in $\mu V^2/Hz$ was computed for the different frequency bands using the multitaper method. The frequency bands were defined for every subject individually.

The peak was determined in a fixed frequency band using the frequency ranges (Samima & Sarma, 2019), which are showed in Table 1. Peaks were detected using Brain Vision Analyzer 2.2 (Brain Products GmbH, Gilching, Germany).

The electrodes were chosen based on the expected changes with different levels of workload in the individual brain areas (see Sec. 2). For beta and gamma FCz electrode was used for active electrodes and T7 for dry electrodes, since the FCz electrode was set to GND and cannot be recalculated (see Figure 1). T7 was chosen instead, since beta and gamma changes can also be detected in temporal brain regions (Singh, Ponzoni Carvalho Chanel, & Roy, 2021). The peak detection was done for both, low and high workload conditions in the predefined frequency band. Afterwards, the average of both peak frequency values was calculated to obtain a value for defining the frequency band.

Table 1: Used frequency ranges for peak detection.

Frequency	Range (Hz)	Electrode
Theta	4.0 – 8.0	Fz
Alpha	8.0 – 13.0	Pz
Beta	13.0 – 25.0	FCz / T7
Gamma	25.0 – 45.0	FCz / T7

To determine the final individual frequency band, we used a 2 Hz frequency band for theta and alpha with the average values as the centre. For beta and gamma, we used a 4 Hz frequency band around the average values, also using them as the centre.

After all individual frequency bands were determined, the average power within this range was determined for each epoch individually. This was done for all electrodes in the respective relevant brain areas. In Table 2 the used electrodes are listed. FCz was not used for the analysis, in contrast to peak detection, of beta and gamma bands, because for the dry electrode data it does not exist and the used electrodes for analysis should be the same for all data.

Table 2: Electrodes used for analyses of different frequency bands.

Frequency bands	Used electrodes
Theta	F3, F4
Alpha	P3, Pz, P4
Beta/Gamma	F3, Fz, F4, C3, Cz, C4, T7, T8, O1, O2

For statistical analysis, it must be checked whether the data are normally distributed. Hence, the Kolmogorov-Smirnov test was applied. Since it turned out that the data are not normally distributed, the Wilcoxon signed-rank test was used to check for statistical significance. If frequency bands were significantly different, the absolute values were used to see if the conditions (e.g., alpha power for N=1 > N=3) were fulfilled (see Figure 4 for an example).

Also, the TLI was calculated for each subject individually, using the average power over all epochs for theta band of Fz electrode and the average power over all epochs for alpha band of Pz electrode. Although the N-back task is not a typical task for task load, the frequency bands considered for workload are very similar. The TLI can therefore be a first indication of whether a subject's workload level is changing. In addition, a specific task was performed during the N-back task, which affects the workload. Also, a study by Hamann et al. (2023) showed the sensitivity of the TLI for workload. Normal distribution was again tested using the Kolmogorov-Smirnov test. Since there was no normal distribution of the data, the Wilcoxon signed-rank test was used to test statistical significance to see, if the TLI is significant higher for N=3 in comparison to N=1. The TLI was used to show in the first step whether a significant difference in the frequency bands could be seen at all for individual subjects within the different levels of workload before the individual frequency bands were analysed. The TLI was used, since it is often used for workload estimation, even if ratios of frequency bands should be used with caution (Boumann, Hamann, Biella, Carstengerdes, & Sammito, 2023). It can be used in this study because the subjects have to actively perform a task, to which the workload condition is linked.

4 RESULTS

The following section presents the results of the EEG analysis in the frequency domain.

4.1 Task Load Index

The Wilcoxon signed-rank test showed a significant increase of workload between the lowest (N=1) and highest (N=3) task level ($p < 0.04$) over all subjects measured with the gel electrodes. When looking at the individual subjects, a difference in TLI can be seen for all subjects (see Figure 3). For subjects with dry electrodes the TLI was also calculated. However, the sample size is not large enough for a statistically significant statement regarding TLI.

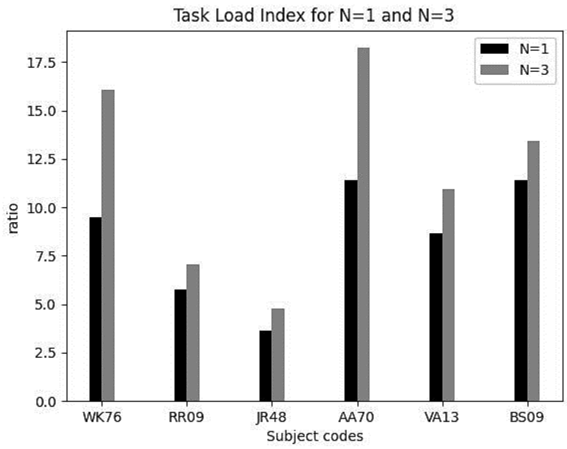

Figure 3: TLI for subjects with gel electrodes for different workload levels.

4.2 Single EEG Bands

We compared the power of the individual EEG frequency bands under different workload conditions (N=1 and N=3) for each subject individually.

For the theta band power, we analysed the F3 and F4 electrodes. We could show a significant increase in the power for four subjects with gel electrodes ($p < 0.003$). For the dry electrodes one subject showed a significant increase ($p < 0.001$). The results can be seen in Table 3.

For the alpha band power, we used the electrodes P3, Pz and P4 and could show a significant decrease in power ($p < 0.03$) for four subjects, but not for the same subjects as for theta power. For the subjects with dry electrodes, we could show a decrease in power of the alpha band for one subject ($p < 0.01$). For subject FW00 the difference between the band power of N=1 and N=3 was significant, but alpha power increased from the lower workload condition to higher workload condition, which can be seen in Figure 4. This value is marked with an asterisk. For individually results of all subjects see Table 3.

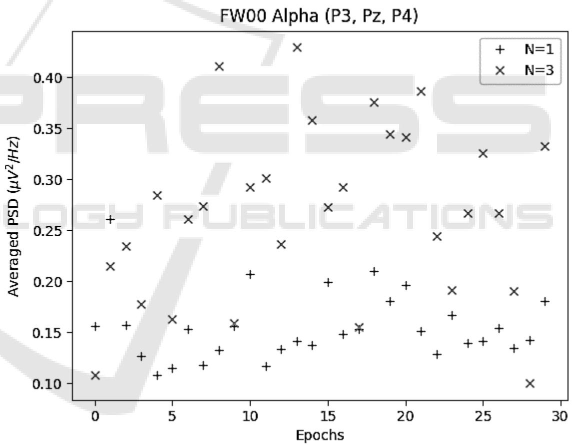

Figure 4: Averaged PSD values for alpha band power of subject FW00 under different workload conditions.

For beta and gamma band power we used the electrodes F3, Fz, F4, C3, Cz, C4, T7, T8, O1 and O2. For beta band power we could show a significant increase in power for one subject with gel electrodes ($p < 0.05$) and for one with dry electrodes ($p < 0.001$). For four of the other subjects the difference between the beta band power was significant, but the power for N=3 decreased in comparison to N=1, instead of increasing. In Table 3, these values are marked with an asterisk as well.

Table 3: p-values for each subject from Wilcoxon signed-ranked test.

Subject	θ	α	β	γ
WK76	<0.001	<0.001	<0.001*	n.s.
RR09	<0.001	<0.03	<0.05	<0.01
JR48	<0.001	<0.001	n.s.	n.s.
AA70	<0.003	n.s.	<0.001*	n.s.
VA13	n.s.	n.s.	n.s.	<0.001
BS09	n.s.	<0.001	<0.003*	<0.001
FW00[1]	<0.001	<0.001*	<0.004*	<0.004
SD50[1]	n.s.	<0.009	<0.001	<0.001

*Significantly different, but power does not change in the direction as expected

[1]Subjects measured with dry electrodes

For gamma band power we could show a significant increase in gamma band power for three subjects with gel electrodes ($p < 0.01$) and for both subjects with dry electrodes ($p < 0.004$). The results for beta and gamma band power can also be seen in Table 3.

5 DISCUSSION

The main objective of this study was to investigate, if an EEG headset system with dry electrodes is suitable for determining workload levels of humans. To test this, we did a study with gel and dry electrodes. Dry electrodes were placed in a custom-made headset optimized to fit a specific person. For this comparison, subjects had to do an N-back task with three conditions (low (N=1), medium (N=2) and high (N=3) workload). For the analysis we only looked into the low and high workload data and compared them with each other.

For data analysis objective measures were used. We did a frequency analysis, because if we find more workload-related and relevant features, these could also be used in addition to the time domain features for machine learning. First the TLI was calculated. As can be seen in Figure 3 a change in TLI, which basically means a change in the ratio between theta band power in Fz electrode and alpha band power in Pz electrode can be seen for all subjects with gel electrodes. The difference is also statistically significant ($p < 0.04$).

Unfortunately, we cannot provide statistics regarding TLI with dry electrodes because the sample size of two subjects is too small. For this, more subjects must be measured with dry electrodes. This was not possible, since the dry electrode headset is customized to fit one person, as mentioned above, and would not fit very well to other subjects. We tried to measure more subjects, but if the size of the head is too small, we could not get any results, because there is no contact between the electrodes and the head surface. If the size of the head is too big, subjects would easily get a headache because of too much pressure. This is definitely a disadvantage of dry electrode headsets compared to gel electrode caps, as already discussed in Trampler et al. (2021), although they are easily to put on by the users themselves.

For the analysis of the power of the frequency bands we used different electrodes for the bands, since the changes of power are detected in different brain areas (Ding, Lu, Lin, & Tseng, 2016; Ding, Cao, Duffy, Wang, & Thang, 2020; Singh, Ponzoni Carvalho Chanel, & Roy, 2021). For beta and gamma frequency we used F3, Fz, F4 and C3, Cz, C4 instead of FC1 and FC2 for fronto-central region, since the dry electrode headset does not have these electrodes and we want to have comparable results.

Based on the analysis, it can be said that the frequency bands have different significance for the analysis of workload. According to the results from Table 3, it can be seen that theta and alpha band power are significant for most of the subjects. At least one of these two frequency bands is significant for all subjects except VA13. For the subjects WK76, RR09 and JR48 even both power changes are significant.

Beta band power has less significance in relation to theta and alpha. Its changes are just significant for two subjects, whereas one was measured with gel electrodes and one with dry electrodes.

Gamma band power changes are significant for five subjects in total, but it is hard to interpret since it is a really high frequency band and its changes could also be affected by muscle activity from frontalis and/or temporalis muscles (Goncharova, McFarland, Vaughan, & Wolpaw, 2003).

Overall, based on our analyses we can state that changes in frequency bands regarding different workload conditions are very subject-specific. This is also important for machine learning, as it makes features very subject-specific as well.

Results from dry electrodes show that there are significant changes in the power of frequency bands. For the subject FW00 we found a significant change in the power of alpha and gamma frequency bands. For subject SD50 we could find significant changes in the power of all frequency bands except alpha. For both subjects we could see a very similar behaviour for dry electrodes compared to gel electrodes.

For future work, the other modalities presented in the introduction (ET, ECG, RESP) should be included to increase the likelihood of the data being useful if the EEG data cannot be recorded properly. The presented modalities also promise a good analysis of the current workload. In addition, the headset must be adapted in terms of cross-subject fit and comfort so that a study with more than two subjects of good data quality can be conducted.

6 CONCLUSION

In this study, we investigated whether the use of dry electrodes to detect workload could be a viable way forward, particularly using a headset that can be very easily self-fitted. Our results suggest that dry electrodes are a promising alternative for the detection of workload if the headset fits the subject. As a next step a study with a larger sample of subjects is needed. However, the adaptability of the dry electrode headsets is significantly less than that of gel electrode caps. To improve this, either better suited subjects with very similar head shapes can be selected or better fitting headsets must be built.

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