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What drives human behaviour? Multimodal eye fixation related brain state analysis for attention and emotion
monitoring

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Peripheral physiological measures such as electrodermal activity (EDA), heart rate and pupil dilation, as well as neurophysiological measures such as electroencephalography (EEG), can inform us about individuals' cognitive and emotional state. We are interested in exploiting such measures in real life situations. A challenge of interpreting physiological measures as markers of mental state in real life is the lack of context information. We here approach this challenge by relating physiological measures to eye tracking. Participants scanned stimuli that induced different levels of workload (small sets of numbers that needed to be added or not) and different types of emotion (neutral, pleasant and unpleasant pictures). EDA, heart rate, pupil size and EEG were related to the first eye fixation on the stimulus. For peripheral measures, response traces across the following 10s were determined and signal amplitudes were compared between the different types of stimuli. EEG signals were compared for the different types of stimuli in the time interval from fixation onset to 1500 ms later using a cluster-based, nonparametric randomization approach. For the peripheral measures, high workload stimuli stood out from all other stimuli in all modalities, with patterns as expected from literature under more traditional experimental conditions: high values of EDA, heart rate, and pupil size for high compared to low workload stimuli. For emotional stimuli, peripheral physiological effects tended to be in the expected direction but were more modest in size. In the EEG signals, a significant late parieto-occipital cluster could be identified with higher amplitudes for high compared to low workload stimuli, as well as for emotional stimuli compared to the neutral stimuli. In future analyses we will combine fixation-locked signals from different modalities to detect mental states elicited by information that is being looked at. Our first results indicate that this may be especially helpful in situations related to cognitive workload, e.g. determining whether operators are not only looking at, but are also cognitively processing information that is presented on a screen.

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Physiological measures such as electroencephalography (EEG), electrodermal activity, heart rate and pupil dilation can inform us about individuals' cognitive and emotional state. A challenge of interpreting physiological measures as markers of mental state in real life is the lack of context information. We approached this challenge by relating the mentioned range of physiological measures to eye movements. Participants scanned stimuli that induced different levels of workload and different types of emotion. Physiology was related to the first eye fixation on the stimulus.
In Brouwer et al. (2020) we showed that high workload stimuli stood out from all other stimuli in all modalities, with patterns as expected from literature under more traditional experimental conditions. For emotional stimuli, peripheral physiological effects were more modest. Our results indicate that fixation related physiology will be most helpful in situations related to cognitive workload.
In Lingelbach et al. (submitted) we focused on applying Multivariate pattern analysis (MVPA). This technique has mainly been

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Contents Final Report

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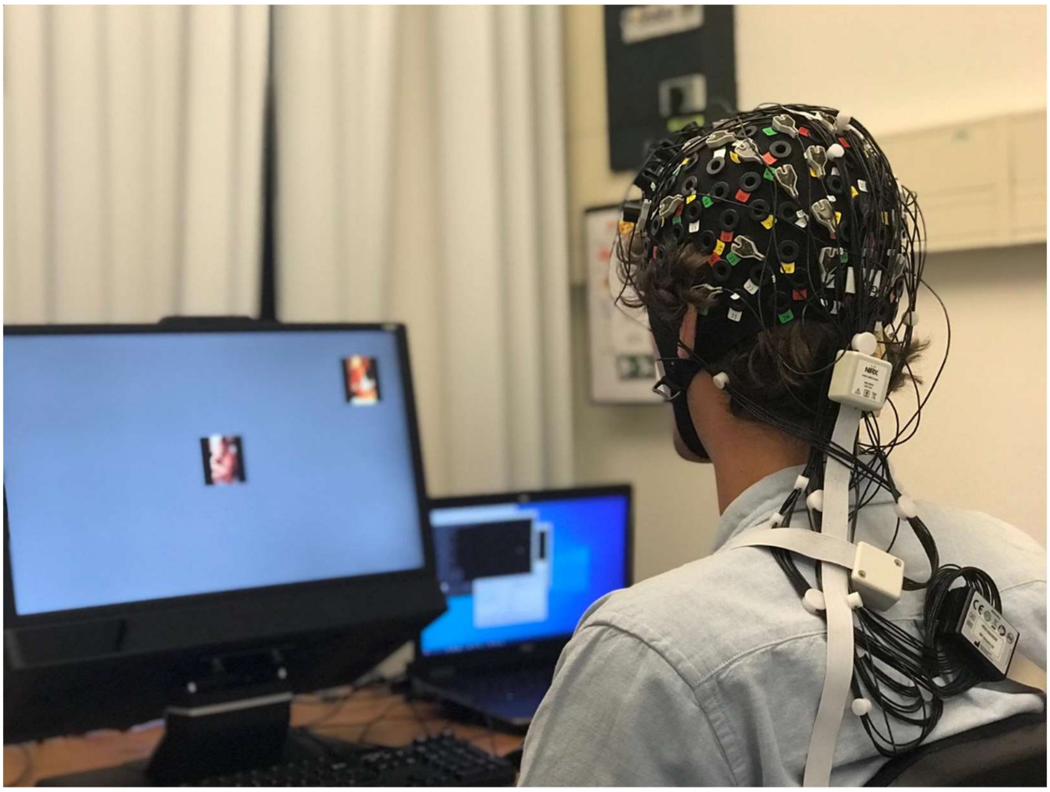
- *Publication 2:* Temporal Decoding of Emotion and Workload from Fixation-Related EEG Recordings
- *Publication 3:* Using Interpersonal Similarity in Complex Networks from Physiological Data to Assess Attentional Focus



Summary and deliverables of project FA9550-19-1-7015

Peripheral physiological measures such as electrodermal activity (EDA), heart rate and pupil dilation, as well as neurophysiological measures such as electroencephalography (EEG), can inform us about individuals' cognitive and emotional state. We are interested in exploiting such measures in real life situations. A challenge of interpreting physiological measures as markers of mental state in real life is the lack of context information. We approached this challenge by relating physiological measures to eye tracking. In a study set up at TNO, participants scanned stimuli that induced different levels of workload (small sets of numbers that needed to be added or not) and different types of emotion (neutral, pleasant and unpleasant pictures). EDA, heart rate, pupil size and EEG were related to the first eye fixation on the stimulus. Functional near-infrared spectroscopy (fNIRS) was originally included in the study as well, using a new system combining EEG and fNIRS. However, due to comfort issues of the fNIRS optodes, this was aborted.

In **Brouwer et al. (2020)** we showed that for the peripheral measures, high workload stimuli stood out from all other stimuli in all modalities, with patterns as expected from literature under more traditional experimental conditions: high values of EDA, heart rate, and pupil size for high compared to low workload stimuli. For emotional stimuli, peripheral physiological effects tended to be in the expected direction but were more modest in size. In the EEG signals, a significant late parieto-occipital cluster was found with higher amplitudes for high compared to low workload stimuli, as well as for emotional stimuli compared to the neutral stimuli. Our results indicate that fixation related physiology will be most helpful in situations related to cognitive workload, e.g. determining whether operators are not only looking at, but are also cognitively processing information that is presented on a screen.

Since single trial analyses for classifying mental state did not show benefit of adding peripheral signals to EEG in this study, we focused **(Lingelbach et al., submitted)** on applying a promising technique for single trial EEG analysis to our data: Multivariate pattern analysis (MVPA). MVPA gives insight into differences in temporal dynamics between elicited mental states. Up till now this technique has mainly been applied to distinguish different sensory processes with rather low-level neuronal representations, and has never been applied to fixation-related EEG. Combining fixation-related EEG with MVPA allowed us to identify the temporal evolution of discrimination success (time decoding) of higher order cognitive processes (emotion and workload) level on a single trial basis. The observed spatial patterns of the coefficients correspond to the few previous (stimulus-locked) reports in the literature, with a stronger contribution of parieto-occipital channels for emotion and fronto-central channels for workload classification.

Another way to provide context for extracting information from neurophysiological signals in real life settings besides using eye fixations, is examining signals of multiple individuals in a group at the same time. Earlier research indicated that high inter-individual similarity (or synchrony) in physiological signals is associated with high outward directed attentional engagement. We collaborated with AFRL to examine alternative ways of re-analyzing data that had been collected at TNO. An extended abstract of this work **(Tolston et al., accepted)** was submitted to the NATO HFM-334 Symposium 'Applying Neuroscience to Performance: From Rehabilitation to Human Cognitive Augmentation'. The work was selected for presentation and invited to extend to a full paper that is currently being written (and will contain the proper acknowledgement statement).

Publications

- Brouwer, A.-M., Stuldreher, I. V., Huertas Penen, S., Lingelbach, K., & Vukelić, M. (2020) Combining eye tracking and physiology for detection of emotion and workload. Volume 1 of the Proceedings of the joint meeting of the 12th International Conference on Measuring Behavior and the 6th Seminar on Behavioral Methods to be held in Krakow, Poland, October 15-18 2021.
- Lingelbach, K., Piechnik, D., Brouwer, A.-M., Stuldreher, I. V., Vukelić, M. (submitted to Neuroergonomics conference 2021) Temporal Decoding of Emotion and Workload from Fixation-Related EEG Recordings.
- Tolston, M. T., Stuldreher, I. V., Funke, G. J., & Brouwer, A.-M. (abstract accepted by NATO HFM-334 Symposium "Applying Neuroscience to Performance: From Rehabilitation to Human Cognitive Augmentation"; invited for full paper) Using Interpersonal Similarity in Complex Networks from Physiological Data to Assess Attentional Focus.

Presentations

- All of the publications above are intended for associated conference presentations. Due to COVID, the Measuring Behavior Conference and Neuroergonomics conference were postponed – they will take place in May 2022 and September 2021 respectively. The NATO conference will be held in October 2021.
- A virtual presentation on the project was given to AFRL on 25 June 2020.

Misc

Two interns (Silvana Huertas Penen at TNO, and Adnan Karol at Fraunhofer) performed their master studies in the context of this project.

Combining eye tracking and physiology for detection of emotion and workload

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Abstract

Peripheral physiological measures such as electrodermal activity (EDA), heart rate and pupil dilation, as well as neurophysiological measures such as electroencephalography (EEG), can inform us about individuals' cognitive and emotional state. We are interested in exploiting such measures in real life situations. A challenge of interpreting physiological measures as markers of mental state in real life is the lack of context information. We here approach this challenge by relating physiological measures to eye tracking. Participants scanned stimuli that induced different levels of workload (small sets of numbers that needed to be added or not) and different types of emotion (neutral, pleasant and unpleasant pictures). EDA, heart rate, pupil size and EEG were related to the first eye fixation on the stimulus. For peripheral measures, response traces across the following 10s were determined and signal amplitudes were compared between the different types of stimuli. EEG signals were compared for the different types of stimuli in the time interval from fixation onset to 1500 ms later using a cluster-based, non-parametric randomization approach. For the peripheral measures, high workload stimuli stood out from all other stimuli in all modalities, with patterns as expected from literature under more traditional experimental conditions: high values of EDA, heart rate, and pupil size for high compared to low workload stimuli. For emotional stimuli, peripheral physiological effects tended to be in the expected direction but were more modest in size. In the EEG signals, a significant late parieto-occipital cluster could be identified with higher amplitudes for high compared to low workload stimuli, as well as for emotional stimuli compared to the neutral stimuli. In future analyses we will combine fixation-locked signals from different modalities to detect mental states elicited by information that is being looked at. Our first results indicate that this may be especially helpful in situations related to cognitive workload, e.g. determining whether operators are not only looking at, but are also cognitively processing information that is presented on a screen.

Introduction

Physiological measures such as skin conductance or electrodermal activity (EDA), heart rate, pupil dilation and electroencephalography (EEG) reflect a range of physical and sensory processes. However, they also contain information about the cognitive and emotional state of individuals [1-3]. This has convincingly been shown in laboratory experiments where participants sit still and are presented by stimuli that are designed to elicit certain cognitive or emotional states. For instance, heart rate is higher and pupil size larger when performing a controlled task with a high memory load compared to performing a low load task [4], heart rate and skin conductance responses differ when pictures with different emotional content are shown [5], and a stronger P300 (a late component in the event-related potential) can be observed for stimuli that draw attention compared to ones that do not [6]. To reliably extract, study and use this information in real life environments, it is important to relate recorded physiological data to context, i.e. to what occurs in the outside world. One way in which this can be done is to use information from eye movements, such as recorded via eye tracking. Recorded fixation locations indicate what is being observed when combined with camera images, or when the visual environment is known in another way (e.g. because certain parts of an information display have fixed locations, or when information is known since it is presented on a monitor). Previous work studied EEG signals related to fixation.

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While this is challenging since eye movements strongly influence EEG, there is now a range of studies showing that higher order cognitive processing of stimulus information during reading and visual search are reflected in such fixation- or saccade related potentials (e.g. [7-9]). Little research has been dedicated to relating other physiological signals to fixations. An exception is [10], who not only related EEG to fixation onset, but also pupil dilation. They found that pupil dilation was higher after fixations on target objects relative to distractor objects, and that this information was helpful besides EEG to classify data as coming from fixations on targets versus distractors. Also, [11] examined both pupil dilation and EEG following fixations on targets and distractors, where participants were asked to remember the locations of the targets while performing an auditory math task. While EEG was especially informative to distinguish between fixations on target and distractor items, pupil size was informative as to whether the target location would be remembered correctly. Specifically, a large pupil size was associated with not remembering the target location, probably because of moments of high workload caused by the math task. We are not aware of work that related EDA and heart rate to fixation onset in paradigms where participants move the eyes around.

As suggested, combining modalities can be helpful to better identify mental state and therewith predict performance. Multimodal measurement techniques can be helpful for different reasons. Firstly, a mental state (e.g. that goes with finding a target, as in [10]) may be better identified when utilizing multiple measures of interest that reflect a similar mental state but are affected by different types of noise. Hence, a combination could result in a more robust identification. Secondly, different modalities can reflect different types of mental state (e.g. event-related potentials in the EEG reflect target detection and pupil size reflects workload as in [11]), enabling more fine-grained mental state estimation. EDA and pupil size are robustly correlated to states of bodily arousal, whereas the P300 component in the EEG reflects states of attention. Peripheral physiological measures may be relatively suitable for emotional engagement (arousal), and EEG (reflecting cortical activity) more for cognitive processes [12-16]. Note that in many cases, these types of processes are expected to coincide: an emotional stimulus is likely to draw attention and a difficult cognitive task likely elicits arousal.

In the current study, we recorded EDA, heart rate, pupil dilation and EEG and related these signals to fixation onset where stimuli are viewed that we expect to elicit different degrees of workload and emotion. Our ultimate aim is to identify affect and cognition in an environment where individuals freely look around so that humans and machines can interact more naturalistic and efficiently. As a first step in exploring and comparing different fixation-locked signals in response to different types of stimuli within the same participants and the same paradigm, we designed an experiment that induced quite predictable and limited amounts of large eye movements. This may be akin to situations of operators who subsequently view portions of a display with information that need to be taken in and induce different types of mental state.

Methods

Participants

A total of 20 healthy participants (5 men, 15 women) took part in this study. They were between 19 and 34 years old, with an average of 23 years. Participants were recruited through the participant pool of the research institute where the study took place (TNO) and received a monetary reward to compensate for time and travel costs. None of the participants wore glasses. All participants signed an informed consent form in accordance with the Helsinki Declaration [17], before participating in the study. This study was approved by the Human Research Protections Official (HRPO) and the TNO Institutional Review Board (TCPE). Eye recording failed in two of the participants, leaving us with fixation-locked data from 18 participants. For the first four participants that we recorded, EDA and heart rate data were lost. In an additional four participants, heart rate data was lost. Four participants were excluded in the EEG analysis due to poor signal quality. In sum, pupil size was obtained for 18 participants, EDA for 14 participants, heart rate for 10 participants, and EEG for 16 participants

Materials

Volume 1 of the Proceedings of the joint meeting of the 12th International Conference on Measuring Behavior and the 6th Seminar on Behavioral Methods to be held in Krakow, Poland, October 15-18 2021. www.measuringbehavior.org.
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For measuring eye gaze location and presenting stimuli, we used a Tobii Pro TX300 eye tracking system (Tobii Technology, Stockholm, Sweden). This system consists of a noninvasive standalone eye tracking recording unit fixed underneath a stimulus screen. Gaze location of both eyes was recorded at 60 Hz. The screen was a 23-inch flat-screen monitor, set at a resolution of 1920 * 1080 pixels. The monitor was about 40 cm from the participants' eyes.

EDA and ECG (electrocardiogram, to obtain heart rate) were recorded using a Biosemi ActiveTwo MkII system, with a sampling frequency of 512 Hz. EDA was measured by placing gelled electrodes on the fingertips of the index finger and the middle finger of the left hand. ECG electrodes were placed on the right clavicle and on the lowest floating left rib. Additionally, we measured neurophysiological activity using EEG. The scalp EEG potentials were recorded using an actiCap 32-channel system according to the extended international 10-05 system with a LiveAmp amplifier (Brain Products GmbH, Munich, Germany). The impedance of the electrodes was kept below 20 kΩ at the onset of each session. EEG data was digitized at 250 Hz, using the BrainVision Recorder Software (Brain Products GmbH, Munich, Germany). The unified collection of signals from the different recording systems and the stimulus presentation program were synchronized and stored for off-line data analysis using Lab Streaming Layer (LSL) [18].

Stimuli and design

Participants were presented with pictures that were expected to induce different levels of workload and types of emotion. There were five types of these pictures: 1) inducing workload: displaying three three-digit numbers arranged around the letter 'A' indicating that these numbers needed to be added (NumbersAdd), 2) inducing no workload: displaying three three-digit numbers arranged around the letter 'N' indicating that these numbers did not need to be added (NumbersNone), 3) inducing pleasant emotion: a picture from the International Affective Picture System (IAPS) [19] with high valence and high arousal (HVHA), 4) inducing unpleasant emotion: a picture from the IAPS with low valence and high arousal (LVHA), 5) inducing no emotion: a picture from the IAPS with neutral valence and low arousal (Neutral).

From the IAPS, the pictures were randomly drawn out of collections of 60 pictures with valence scores higher than 5.5 and arousal higher than 5.5 (pleasant), valence scores lower than 4.5 and arousal higher than 5.5 (unpleasant) and valence scores between 4.5 and 5.5 and arousal lower than 4.5 (no emotion or neutral).

All pictures were approximately 205 by 154 pixels in size and could appear at any of 9 locations on the screen, with a minimum distance of 191 pixels between two sequentially presented pictures. A picture was presented for 10 s. Nine seconds after picture onset, the next picture appeared. Workload inducing pictures could be followed by a screen prompting the participant for the result of the addition. This was intended to motivate participants to really perform the math during the workload inducing picture, and to allow them a short break. Blocks of stimuli separated by these questions consisted of 15 or 20 pictures, containing 3 or 5 pictures, respectively, of each type. Otherwise, the order of pictures was random. Participants finished up to 14 blocks (with a minimum of 12 blocks, and a median of 14 blocks).

Procedure

Participants received a short explanation about the study and were invited to ask any question they may have. They then signed the informed consent form. The Tobii eyetracker was calibrated using a nine-point calibration. Participants were fitted with the ECG, EDA and EEG electrodes. Participants were asked to not speak during the experiment unless absolutely necessary and to keep movements to a minimum.

Analysis

All data analysis was performed with custom written or adapted scripts in MATLAB® and Python™ .

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For the EDA, the phasic and tonic components were extracted using Continuous Decomposition Analysis [19] as implemented in the Ledalab toolbox for MATLAB®. The phasic component was z-score standardized following [21]. These data are further used in the analysis.

ECG measurements were processed to acquire the inter-beat interval (IBI, which is the inverse of heart rate). ECG was band-pass filtered between 5 and 15 Hz using a third order Butterworth filter. Peaks were detected following Pan and Tompkins [22]. The IBI semi-time series was transformed into a timeseries. This was done by interpolating consecutive IBIs and then resampling at 512 Hz. IBI was then transformed to heart rate and further used in the analysis.

To handle missing values in the raw eye tracking data (pupil size and gaze location), typically occurring due to blinks, the data were linearly interpolated in time windows of maximum 75 ms of consecutive missing data points [23]. Data from the left and right eye were averaged [23-24]. Additionally, gaze position was smoothed using a median filter with a sliding window of 20 ms [24]. Gaze position over time was used to determine fixation onset, where we are interested in the first fixation on the picture. In order to do this robustly without having to rely on more or less arbitrary temporal and spatial thresholds, we followed a previously adopted approach [11,25] and determined the time of the maximum velocity of the saccade of interest as a proxy of fixation onset, though note that the actual fixation starts in the order of 30 ms later. For convenience, we still refer to our data as 'fixation-locked' rather than 'saccade-locked'. Maximum saccade velocity was searched for in a 1.5 seconds window, starting at the onset of the new picture. Note that this method takes advantage of the design of our experiment by providing us knowledge of the approximate time of fixations of interest. It should be replaced by another method in situations with more unpredictable timing - e.g., in the case of a known display, fixations of interest are those associated with saccades that moved the gaze from outside into a certain spatial area of interest; or generic temporal and spatial thresholds should be used.

For each picture, EDA epochs were extracted, starting at time of fixation and ending 10 seconds later. For each participant, these epoched signals were aligned by subtracting the average value of the first 500 ms from the epoched signal, and averaged across pictures of each of the five picture types (HVHA, LVHA, Neutral, NumbersAdd and NumbersNone). The same procedure was followed for heart rate and pupil size. Next, for each participant and picture type, the response amplitude was determined by taking the maximum value in the epoch for EDA and heart rate, and by taking the average value in the epoch for pupil size. These data are used in statistical analyses.

To analyze the neurophysiological data, EEG signals were de-trended, zero-padded and re-referenced to mathematically linked mastoids [26]. We excluded two EEG channels (T8 and T7) from the analysis due to artefact contamination. Next, we band-pass filtered the EEG signals between 1 to 20 Hz to calculate fixation-locked event-related potentials (FERP). The filtering was done by using a first order zero-phase lag finite impulse response (FIR) filter.

For the analysis of FERPs, fixation-locked epochs ranging from 200 ms before and 1500 ms after the beginning of the fixation onset were created separately for the five picture types (HVHA, LVHA, Neutral, NumbersAdd and NumbersNone). We rejected epochs containing a a maximum deviation above 200 µV in any of the frontal EEG channels (AFp1, AFp2). Furthermore, for each remaining epoch we performed an independent component analysis (ICA) using the extended infomax ICA algorithm [27] as implemented in the MNE-Python toolbox [28]. The ICA was used to remove further cardiac-related artefacts, ocular movement and muscular artefacts. The selection of components indicating artefacts was done by careful visual inspection of the topography, times course and power spectral intensity of the components [29,30].

To study spatio-temporal changes of neurophysiological signals we baseline-corrected the artefact-free EEG epochs by subtracting the mean amplitude of the time interval between -200 ms and 0 ms before the fixation onset. FERPs were then calculated by averaging the EEG signal separately for each picture type (HVHA, LVHA, Neutral, NumbersAdd, NumbersNone) and each channel. For the statistical evaluation we performed a mass-univariate analysis. We chose a cluster-based, non-parametric randomization approach which included

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correction for multiple comparisons as described by [31] and implemented in the MNE-Python toolbox [28].We compared the baseline corrected data from all electrodes at all time points after the fixation onset to locate effects of emotional pictures (comparing Neutral vs HVHA and Neutral vs LVHA) and workload pictures (comparing NumbersAdd vs NumbersNone) in time and space. Clusters were identified as adjacent points in space (electrodes) and time (time point in the EEG segment) using a cluster-level threshold of $p<.01$ estimated via a t-test (uncorrected). The cluster-level statistics were defined as the sum of t-values within every cluster. The correction of multiple comparisons was realized by calculating the 95th percentile of the maximum values of summed t-values estimated from an empirical reference distribution. T-values exceeding this threshold were thus considered as significant at $p<.05$ (corrected). The reference distribution of maximum values was obtained by means of a permutation test (randomly permuting the data points across the compared condtions for 1000 times). Thereby, we perform the statistics separately for the emotional and workload pictures.

For each physiological modality, we specifically compare responses to pictures with numbers, and responses to neutral versus emotional pictures, since these types of pictures differ only with respect to the emotional or cognitive state that they are expected to induce, and are similar with respect to other, low-level stimulus characteristics.

Results

Figure 1 shows the traces, averaged across participants and picture type, for EDA (A), heart rate (B) and pupil size (C). Especially NumbersAdd stimuli elicit clear responses in all three modalities.

Figure 2 presents the average of the response amplitude for EDA, heart rate and pupil size. Because our data were not normally distributed, non-parametric tests were used for statistical comparison. Wilcoxon signed rank tests indicated that EDA amplitude is significantly higher for high workload pictures, with numbers to add (Mdn = 0.379) than for low workload pictures, with numbers not to add (Mdn = 0.172). The same result was found for HR amplitude (Mdn = 3.707 for NumbersAdd and Mdn = 3.125 for NumbersNone) and for pupil size amplitude (Mdn = 0.411 for NumbersAdd and Mdn = 0.138 for for NumbersNone). Regarding emotional pictures, EDA amplitude is higher for low valence pictures (Mdn = 0.066) than for neutral pictures (Mdn = 0.032). There is a small trend in the same direction for high valence versus neutral pictures. No statistically significant differences were found in heart rate and pupil size amplitudes when comparing high valence pictures to neutral pictures, and when comparing low valence to neutral pictures. An overview and details of the statistical results are given in Table 1.

For EEG, using the non-parametric cluster-based randomization test, we found one significant late parieto-occipital electrode cluster for the comparison between the neutral pictures against the pictures with high valence (Figure 3A). This cluster comprised 15 electrodes with a difference from 164 ms to 912 ms after fixation onset. Similarly comparing the neutral pictures versus the pictures with low valence, we observed one significant late parieto-occipital electrode cluster (Figure 3B). The cluster comprised 17 electrodes with a difference from 160 ms to 1000 ms after fixation onset. Comparing the NumbersAdd and NumbersNone pictures, we found one significant cluster over parieto-occipital electrode regions (Figure 4). The parieto-occipital comprised 12 electrodes with a difference from 252 ms to 672 ms after fixation onset.

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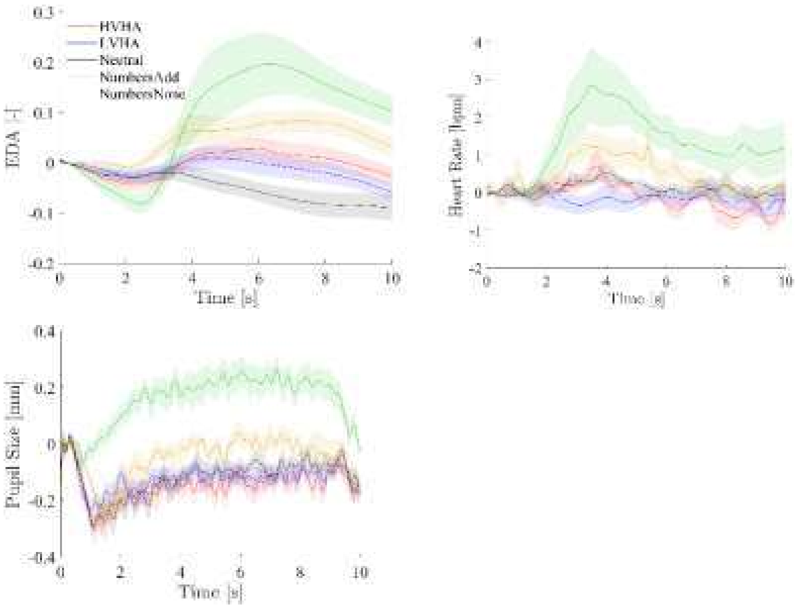

Figure 1. Response traces (average and standard error of the mean) time-locked to fixation onset for EDA (A), heart rate (B) and pupil size (C). Red traces represent HVHA pictures; blue LVHA; black Neutral; green NumbersAdd; yellow NumbersNone.

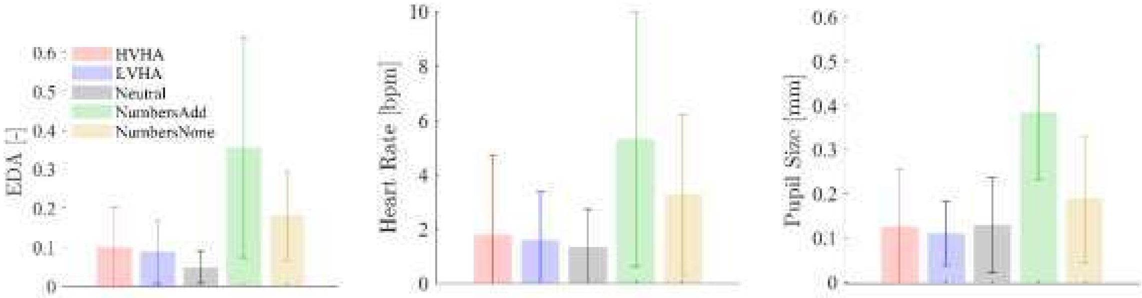

Figure 2. Average response amplitude in response traces time-locked to (from left to right) HVHA, LVHA, Neutral, NumbersAdd and NumberNone pictures, for EDA (A), heart rate (B) and pupil size (C). Error bars represent standard errors of the mean.

	EDA	Heart rate	Pupil size
NumbersAdd vs. NumbersNone	$\mathbf{W = 121, p = .006}$	$\mathbf{W = 65, p = .043}$	$\mathbf{W = 147, p = .007}$
HVHA vs. Neutral	$W = 100$, $p = .098$	$W = 44$, $p = .733$	$W = -82$, $p = .879$
LVHA vs. Neutral	$\mathbf{W = 106, p = .049}$	$W = 50$, $p = .424$	$W = 66$, $p = .396$

Table 1. Statistics for comparison between stimulus types, for EDA, heart rate and pupil size.

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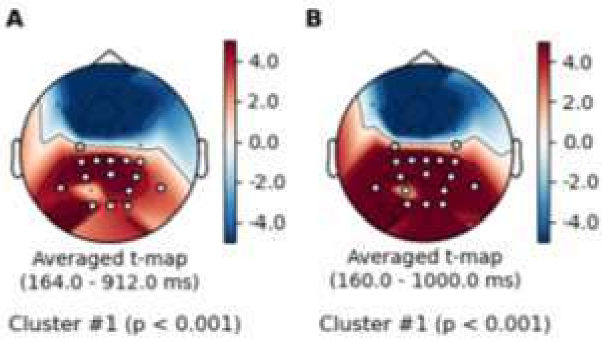

Figure 3. Spatio-temporal dynamics for the emotional pictures. The plots show the topographic maps of the t-values that represent the difference comparing the neutral with the positive (HVHA) pictures in (A) and the neutral with the negative (LVHA) pictures in (B). Electrode clusters showing significant differences in the non-parametric randomization test, are indicated by filled white circles. In both comparisons, an extended late parieto-occipital cluster was found. The amplitudes of the FERPs were larger for the positive (HVHA) and negative (LVHA) pictures than for the neutral pictures.

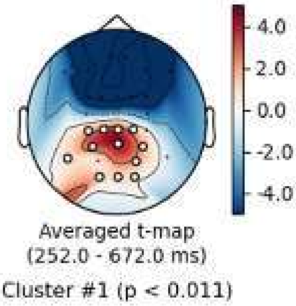

Figure 4. Spatio-temporal dynamics for the workload pictures. The plot show the topographic map of the t-values that represent the differences comparing the numbers not to add (NumbersNone) with the numbers to add (NumbersAdd). Electrode clusters showing significant differences in the non-parametric randomization test, are indicated by filled white circles. The non-parametric randomization test reveals an extended late parieto-occipital cluster. The amplitudes of the FERPs were larger for the NumbersAdd compared to the NumbersNone condition.

Discussion

We examined EDA, heart rate, pupil size and EEG related to fixations on stimuli that were expected to induce different levels of workload and types of emotion.

For all three peripheral physiological measures, we found the expected increase when comparing high workload stimuli (NumbersAdd) to stimuli with the same visual appearance, but without an associated mental workload task (NumbersNone). The average EDA stimulus traces for emotional and neutral pictures showed the expected pattern with larger values for emotional (high arousal) pictures compared to neutral pictures. The heart rate patterns are roughly consistent with those reported in [5], where heart rate was examined in response to IAPS pictures without having participants move their eyes towards the pictures. They also found an acceleration starting at around 2 seconds for pleasant pictures, followed by a strong deceleration at around 3.5 seconds, whereas unpleasant pictures show more of a deceleration, and heart rate responses to neutral pictures were closer to those to pleasant compared to unpleasant ones. However, our statistical analyses on the overall amplitude did not show significant effects for heart rate – only for EDA the comparison between neutral and high valence, high arousal pictures reached significance.

For the EEG fixation-locked dynamics, we found a late parieto-occipital cluster sensitive to pictures inducing high and low valence compared to neutral pictures. A similar effect was found for high versus low workload inducing pictures. These findings are consistent with earlier studies. Previous studies consistently find higher amplitudes in late components for high compared to low arousing affective pictures (where P300 and later slow

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wave potentials elicited with affective pictures are often denoted as late positive potential or LPP) [32-34]. Concerning the high and low workload pictures in our study, high workload pictures are expected to induce arousal, attentional and working memory processes, which are processes that are associated with higher amplitudes in late parieto-occipital components [6,35]. Note that in our case, the participant finds out during the first fixation on a high workload picture that a mental task has to be performed, i.e., that the picture is particularly relevant. This is a different case than most EEG workload studies, in which stimuli such as beeps are usually associated with low rather than high P300 amplitudes. In these studies, high workload as e.g. induced by a double task, prevents participants to allocate much attention to the presented stimuli [36,37], which is consistent with a low P300.

Performing a mental task (adding numbers) seems to induce immediate and stronger arousal compared to viewing pictures that may not have direct relevance to the particular participant, and are not related to any (upcoming) action. Arousal due to an upcoming, socially relevant emotional task can expected to be stronger than emotion induction through pictures [38]. Fixation-related physiology may especially be helpful in situations related to cognitive workload, e.g. determining whether operators are not only looking at, but are also cognitively processing information that is presented on a screen; or in situations involving strong, personally relevant emotions that are related to upcoming action.

To bring fixation-locked physiology closer to applications, several steps are required. In following analysis, we will examine whether on an individual level, for a single fixation, a classification algorithm can estimate which of the five picture types an observer is looking at – i.e., identify an individual's mental state using combined multimodal fixation locked measures. Combining modalities may aid to get a more strongly differentiating signal.

For this first EDA, heart rate and pupil size fixation locked study, we wanted to heighten the chance that participants dwelled on a certain stimulus for some time, which is why we presented stimuli on different locations but sequentially, with only a short time of simultaneous presence on the screen. Figure 1 suggests that minimum gaze times of 4 to 6 seconds would suffice to obtain an undisturbed maximum signal. A more ecological experiment would entail the presentation of multiple stimuli on the screen at once, e.g. in an operational setting where an observer has to monitor and interpret different parts of a display.

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Temporal Decoding of Emotion and Workload from Fixation-Related EEG Recordings

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Motivation and Aim: Electroencephalographic (EEG) recordings allow to capture temporal activation patterns associated with the current level of workload or emotional states [1-4]. Decoding mental states from these activation patterns and reacting to them accordingly can increase performance, safety, and user experience during human-machine interactions, e.g., in medical surgery or autonomous driving. In such naturalistic environments, it is particularly important to integrate context information and identify the current locus of attention to achieve robust mental state decoding. When combining EEG signals with information regarding the eye movements acquired via eye-tracking, the analysis of neuronal temporal dynamics can be related to the fixation on or saccade towards a stimulus [5-9].

Multivariate pattern analysis (MVPA) receives increasing attention since it allows to distinguish subtle differences in temporal dynamics between conditions [10-11]. MVPA has mainly been applied to distinguish different sensory processes with rather low-level neuronal representation (e.g., [8,12-14]), especially in functional magnetic resonance imaging (fMRI). However, because of their high temporal resolution, magnetoencephalography (MEG) and EEG are particularly suited to unravel fine-grained temporal dynamics [10-11]. In a recent MEG study on elementary arithmetic, Pinheiro-Chagas and colleagues [15] used MVPA to successfully distinguish between successive additions vs. subtraction. Few studies examined temporal dynamics associated with emotional processing [16-17]. To the best of our knowledge, no study combined eye-tracking with EEG to investigate a fixation-related temporal decoding of higher cognitive processes.

Therefore, we here investigate spatio-temporal dynamics of different emotional states and workload levels within a MVPA approach on fixation-related EEG recordings. We are interested whether we can distinguish between (a) emotional states when processing images with positive, neutral, and negative valence and (b) low and high workload.

Methods: Participants moved their eyes to pictures or pairs of three-digit numbers that were positioned on trial-by-trial alternating locations on the screen (cf., [5]). Emotional states were induced using pictures from the International Affective Picture System (IAPS) [18] which were of low (LVHA), average (neutral), and high (HVHA) valence and high arousal (XXHA). To induce different workload levels, participants had to either perform an elementary calculation by adding the two numbers (numbersA; high workload) or solely watch the numbers (numbers; low workload). Each stimulus was presented 10 s with an overlap of 1 s with the next stimulus. Participants performed 14 blocks with 15 or 20 stimuli per block. EEG was measured with 32 channels from 16 participants (12 female, 4 male, age of M = 22.2, SD = 4.1, range: 19 and 34 years).

The EEG signals were de-trended, zero-padded, and re-referenced to mathematically linked mastoids [19]. The channels T8 and T7 were excluded due to artefact contamination. Next, we band-passed (1 - 20 Hz) the signals using a zero-phase lag finite impulse response (FIR) filter. Data were cut into 3 s epochs starting at the fixation-onset, including a 200 ms baseline. Epochs with strong artefacts were rejected (maximum deviation above 200 µV in AFp1, AFp2). Further cardiac-, ocular-, and muscular-related artefacts were removed using an independent component analysis (ICA) as implemented in the mne toolbox [20].

For the time decoding, we used the xDAWN algorithm [21-22] as implemented in mne with two components to increase the signal-to-noise ratio by estimating spatial filters and applying them to the signal. Next, signals were downsampled (200 Hz) and baseline corrected. To distinguish the workload levels and emotional states, we compared conditions pairwise as a binary classification problem (HVHA vs. neutral, LVHA vs. neutral, HVHA vs. LVHA, numbers vs. numbersA) using a logistic regression (LR) with L2 regularization and liblinear as solver (implemented via scikit-learn; [23]). We compared the results to: (a) an empirically estimated chance level (dummy classifier) and (b) a theoretical chancel level as suggested by [24]. Classifier performance was evaluated per participant within a Monte Carlo Simulation (MCS) with 100 iterations, stratified 5-fold cross validation for each time point, and area under the receiver operating characteristic (ROC) curve (AUC) as metric (Figure 1A). For spatial interpretation, we used the weight vectors (coefficients) of the classifier models, as implemented in mne [20,25] (see Figure 1B).

Results and Discussion: Our results reveal above-chance level decoding performance of the emotional states starting 200 ms to 700 ms after fixation onset (HVHA vs. neutral: max AUC = 0.927 at 352 ms; LVHA vs. neutral: max AUC = 0.893 at 420 ms; HVHA vs. LVHA: max AUC = 0.885 at 288 ms). During the workload condition, the above-chance level decoding time window is 200 to 580 ms (max AUC = 0.921 at 352 ms; Figure 1A). The topographical plots of the spatial patterns indicate that parieto-occipital channels mainly contributed to the decoding when contrasting HVHA to LVHA and neutral (Figure 1B); while frontal channels were mainly associated to neutral and LVHA contrasted to HVHA. For the decoding of the workload condition, most discriminative channels were distributed over fronto-central regions. The decoded time windows and spatial patterns are in line with studies on event-related potentials associated with emotional processing and workload such as the P300 and late positive potential (LPP) [5,26-29].

Our proposed method to combine fixation-related EEG with MVPA allowed us to identify the temporal evolution of discrimination success (time decoding) of higher order cognitive processes such as emotion and workload level on a single trial basis. The observed spatial patterns of the coefficients correspond to those reported in the literature with a stronger contribution of parieto-occipital channels for emotion and fronto-central channels for workload classification. In the long term, our research aims to recognize cognitive and emotional states in naturalistic and complex environments by combining context information with sensitive and robust decoding methods. In the next step, we plan to investigate temporal generalization, or performance stability, of one classifier trained at one time point when testing it on all other time points [10-11,15].

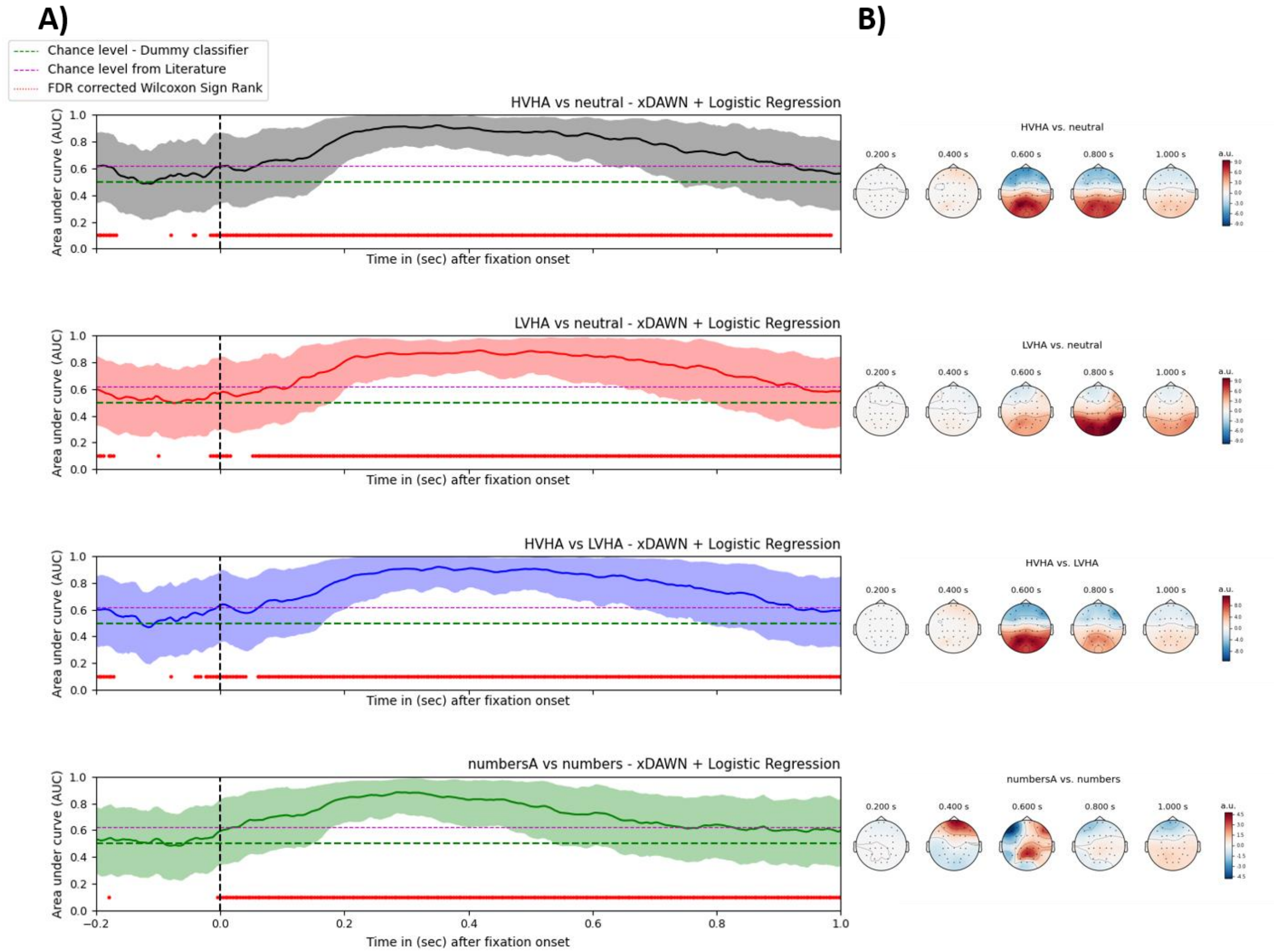

Figure 1. Temporal decoding of a logistic regression to discriminate emotional states and workload levels. A) Grand-average classification performance of the Monte Carlo Simulation (MCS; 100 iterations) measured with the metric Area Under Curve (AUC) and averaged across subjects, folds, and iterations. Shaded areas represent the 5 and 95 percentiles. Dotted purple line: Theoretical chance level at 0.62 [24]. Dashed green line: Dummy classifier with stratified as method. Red dots: Significant time points examined via a Wilcoxon Sign Rank test (one-sided) with False Discovery Rate (FDR) correction for multiple comparisons and a significance level at α = .01 comparing the average classification performance of the MCS tested against the empirical chance level. B) Topographical plots represent the spatial patterns of the coefficients from the decoding models.

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Using Interpersonal Similarity in Complex Networks from Physiological Data to Assess Attentional Focus

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With military teams moving into increasingly dynamic environments and organizational structures, it will be critical to evaluate joint attention and similarity of task investment so that effective teamwork interventions can be designed. However, measuring shared attentional constraints in complex environments is quite difficult [1]. Using techniques that can evaluate similarity in complex and potentially multivariate data sources can help with this problem. In the present work, we used such an approach to re-evaluate existing data collected from individuals listening to a 66 minute long audiobook while also occasionally being presented with affectively salient or cognitively demanding stimuli [2]. In order to uncover the effects of attentional focus on dynamics of physiological data, we used a complex network approach to evaluate the similarity in physiological responses as a function of whether individuals were instructed to attend to the stimuli or to attend only the audiobook.

Heart rate data from 26 participants were analyzed in this study. Data were split into two-minute epochs with 87.5 % overlap. In each window, recurrence quantification analysis was conducted to create a complex network representation of the system dynamics. Recurrence plots were used to assess similarity between networks using average mutual information [3]. Average values of similarity between an individual's time series and the time-series of all other individuals in the same condition (intra-group similarity) or the other condition (inter-group similarity) were calculated. These values of intra- and inter-group similarity were entered into a mixed ANOVA, with similarity-type (intra, inter) as the within subject's variable and stimulus attending condition as the between subject variable.

Results showed a significant similarity-type × stimulus-attending interaction, $F(1,24) = 164.50$, $p < .001$. Simple main effects analyses showed that, for the group that were instructed only to attend the audiobook, intra-group similarity ($M = 0.371$, $SD = 0.020$) was lower than inter-group similarity ($M = 0.376$, $SD = 0.022$), $F(1,12) = 56.252$, $p <.001$. However, for the group that were instructed to attend the stimuli, intra-group similarity ($M = .380$, $SD = .017$) was higher than inter-group similarity ($M = 0.376$, $SD = .018$), $F(1,12) = 159.81$, $p < .001$.

Individuals instructed to attend the stimuli had physiological dynamics that were more similar to others in their own group, while individuals who were told to ignore the stimuli showed the opposite pattern. Investigation of the data showed that the presented stimuli evoked regular responses in the stimulus attending group and less regular responses (i.e., at varying times) in the non-attending group. This is consistent with the notion that the stimuli attracted the attention of all individuals, but more consistently so in individuals who were told to attend to them. We believe these analyses can identify characteristic responses and can help identify when individuals may be distracted from a task. We are currently investigating the complementary nature of these recurrence quantification analyses and those based on instantaneous synchrony. Furthermore, we are moving to incorporate the full set of multivariate data collected in this study that includes EEG and electrodermal activity.

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