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 results of the event-related potential (ERP) analysis [5] and further studies investigating ERPs associated with emotional processing and workload such as the P300 and late positive potential (LPP) [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 decoding multiple classes within one model as well as temporal generalization, or performance stability, of one classifier trained at one time point when testing it on all other time points [10-11,15].

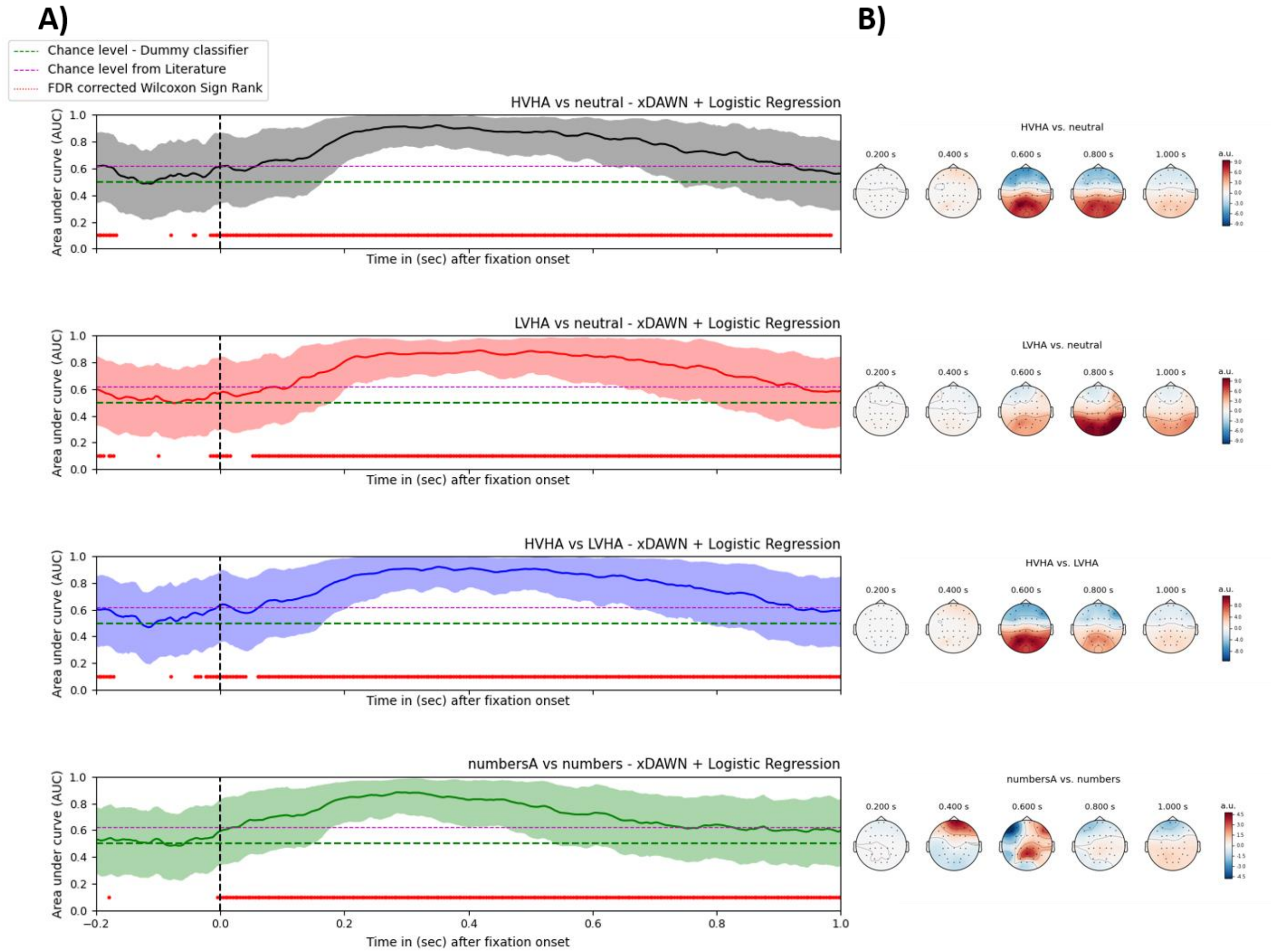

Figure 1. Temporal decoding of a logistic regression to discriminate emotional states and workload levels. A) Grand-average classification performance of the Monte Carlo Simulation (MCS; 100 iterations) measured with the metric Area Under Curve (AUC) and averaged across subjects, folds, and iterations. 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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