Continuous Mental State Detection for Mental Ergonomics

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Unlike in many robotic applications that require complete autonomous operation (Eich et al. 2010 and Aggarval et al. 2015), in human-robotic interaction systems effects of robots on the work environment become more and more relevant. Solutions must be found to reduce physical stress, but mental stress has to be studied to improve ergonomics. For this purpose, methods must be developed to continuously detect cognitive load (Kirchner et al. 2016, Neu et al. 2018). In the KAMeri project, we focus on improving occupational safety by analyzing the human's electroencephalogram (EEG) and adapting human-machine interaction according to a worker's cognitive state. Safety-relevant mental states such as fatigue and workload are detected to adjust the robot's behavior. We present results on the data quality of a tailor-developed headset for EEG recording with dry electrodes and on our training classifiers within established psychophysiological paradigms to continuously detect different mental states.

Neuroergonomics is defined as "the study of the human brain in relation to performance at work and everyday settings" (Parasuraman, 2003). Never-ending open questions are easiness of use and comfort issues (Gramann et al., 2017). We developed a headset that is possible to put on with just one movement, with twenty-four dry electrodes (Fiedler et al. 2015), including ground (GND) and reference (REF), so that the setup time is less than 10 seconds. To improve the comfort, we considered different head shapes (Lacko et al., 2017) and optimal pressure between electrodes and scalp (Fiedler et al. 2018). In this line, we have created a pipeline that: 1. creates an individual mesh from a subject's head; 2. finds the individual 10/10 position (Oostenveld et al.,2001); 3. adapts the model of the headset to these positions. Every electrode is positioned by an arch that adapts its pressure at the proper force (see Fig. 1). One EEG headset was built up to fit one test person. We tested the headset with the subject it was made for (subject S1), a subject with a similar head size and shape (S2), one with a larger head (S3), and two subjects with smaller head sizes and different shapes (S4 and S5).

To test the data quality, we used a previously developed scenario where the subjects were asked to respond to target stimuli presented in an oddball fashion with a buzzer press for single-trial detection of P300 (Ghaderi et al., 2014) and the lateralized readiness potential (LRP) detected before the buzzer response (Kirchner et al., 2014). We compared a gel-based 64-channel cap on six subjects versus the headset with dry electrodes on S1 and S2 (see the outcomes of the recordings below). We were able to reach a balanced accuracy (BA) (Straube et al. 2011) of 0.938 ± 0.019 BA with the gel cap (Ghaderi et al., 2014), while we had a BA of 0.826 for subject S1 and a BA of 0.882 for subject S2 using the same amount of training data and the same preprocessing flow as in Ghaderi et al., 2014. Furthermore, with the gel-based cap, the LRP had a BA of 0,935 ± 0,036 (Kirchner et al., 2014), while with the headset, 0.895 BA for S1 and 0.91 BA for S2.

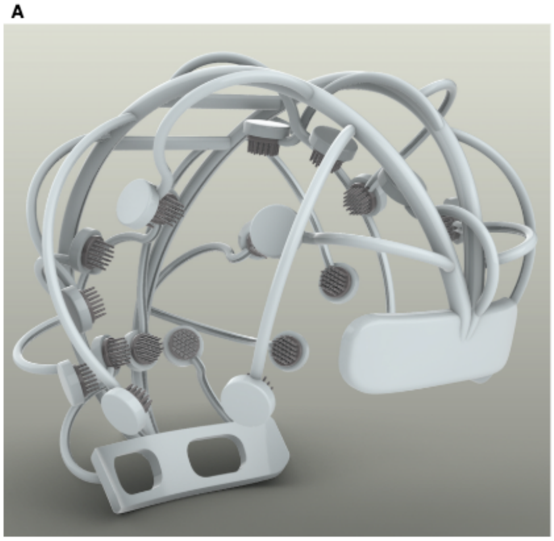
To train the classifiers to detect specific mental conditions, we chose some psychophysical paradigms (Gevin et al.1979) relevant in our application: N-back task (N= 1,2, and 3) (Kirchner 1958), mental rotation task (time limit: 20 s, 10 s, and 3 s) (Shepard and Metzler 1971), mental calculation task (10 s time limit; addition and subtraction: 1-digit, 2-digit, and 3-digit numbers), and, at the end of each of the three trials with increasing cognitive effort, a Stroop task (Stroop 1935) to detect effects of fatigue on attention. As ground truth for mental load, subjects filled in the NASA task load index (NASA-TLX) (Hart and Staveland 1988) after each run.

Other studies (Keirn and Aunon, 1990) used spectral EEG parameters to distinguish between mental tasks. We adopted an overlapping 3s windows to calculate the PSD for each of the 22 EEG channels to generate Gradient Boosting regression/classification features. For preprocessing, the data were down sampled to 160Hz and bandpass filtered between 0.1 and 40Hz. As a target, we used the mean across the NASA-TLX scales.

During the one-hour data acquisition, we had to stop recording subject S3 after 20 minutes due to pain from the pressure. For all other subjects, EEGs were recorded entirely. Manual inspection of the data showed that no clean EEG was recorded for subjects S4 and S5. The pressure of the dry electrodes on the scalp was too low.

In summary, a simple and fast method to acquire a good EEG signal quality could be achieved using a custom-made headset with dry electrodes. It can easily be placed by the subject itself. The headset, when it fits well, can be worn easily for at least two hours. The customized approach looks promising for helping in reaching the balance between easiness and quality of data. The performance in single-trial P300 and LRP detection was very close to the 64 wet electrodes, even using only 24 dry electrodes, including REF and GND. As a preliminary result, we could show that NASA-TLX values partially correlate with the workload estimated from the EEGs (results in Figure 2 A and B based on EEGs from subjects S1 and S2). Further, the level of difficulty of the Stroop data sets could be predicted with very high precision (see Figure 2 C), suggesting that the level of fatigue could be classified from the EEG. Next, we will record more data and test our approach to detect mental load in everyday work activities, e.g., working on a PC, talking to other people, looking at complicated CAD construction, or controlling a device. Finally, we will compare the results recorded with the dry electrode headset with EEG data recorded with gel-electrodes for the same subjects.

A



B

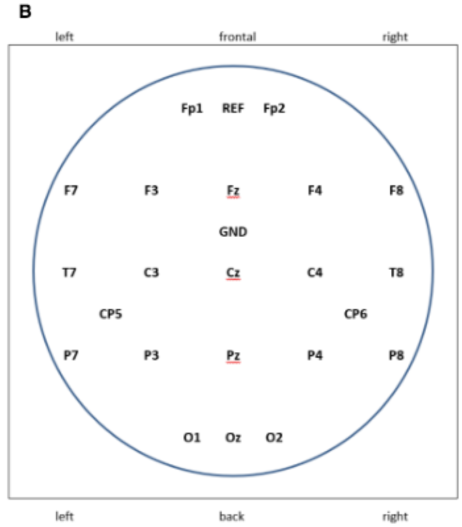


Figure 1: A: Headset design with integrated dry electrodes; B: Electrode layout.

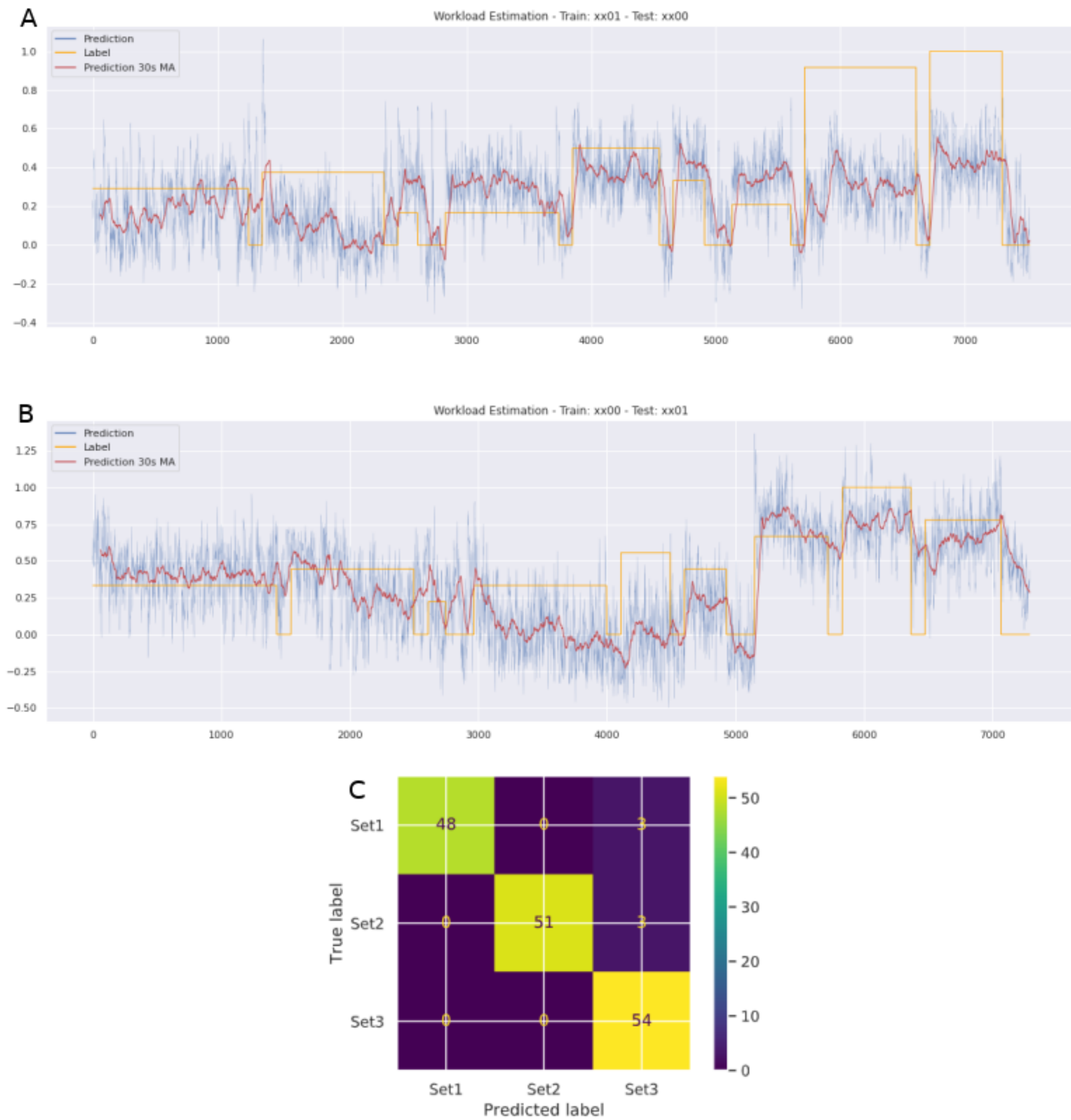


Figure 2: A/B: Subject vs. Subject results for the workload estimation all sets concatenated. Orange: Target, Blue: Single prediction, Red: 30s Moving Average. C: Fatigue classification performance during Stroop Test based on predicting the corresponding set.

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