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Cognitive workload BCI in the maritime environment

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Introduction: The human factor plays the key role for safety in many industrial and civil every-day operations in our technologized world. Human failure is more likely to cause accidents than technical failure, e.g. in the dangerous job of tugboat captains. Here, cognitive workload is crucial, as its excess is a main cause of dangerous situations and accidents while being highly subject and situation dependent. However, reliable subjective ratings are hard to obtain while objective ratings remain a necessity for training as well as control, port and operation design – leading to a high general interest in online cognitive workload indicators.

Material, Methods and Results: In a 10-subject simulator study, we recorded electroencephalographic data from a realistic tugboat scenario with professional captains (subj. 8 excl.: sickness). The experiment had 3 phases (approx. 40mins each), where phases 1&3 were identical. While in phases 1&3, the cognitive workload was modulated by the sailing task itself in combination with changing weather conditions, we increased it in phase 2 by an additional task (2-back task [1]) and kept sailing constant (Phase 1&3: 2 blocks 6mins low/12mins high workload. Phase 2: 10 blocks of 4mins high/low). The measurement epochs were designed to lead to similar behavioral patterns. The blocks were subdivided into epochs of 1 min for classification. The classifier was based on regularized shrinkage linear discriminant analysis (rsLDA) [2] after different preprocessing steps. We used 1Hz high-pass filtering alone (**R**), in combination with MARA [3] (**C**), an Independent Component Analysis (ICA) based automatic artifact reduction, as well as manual ICA artifact reduction (**CM**). Then, we built different spectral band power based features. In addition, we performed Common Spatial Pattern analysis (**CSP**) [4] in different band combinations with the logarithm of the variances as features. We evaluated the different classification designs within phases as a block-wise cross-validation (cv) as well as between phases to test for generalization. The results suggest a basic feasibility of binary workload classification with lowest cv-loss in phase 2. For the auditory n-back task (phase 2), higher workload seems connected to increased high visual alpha while results are less clear for the bow-to-bow condition (phase 1&3). Here, we often found an opposite visual alpha effect.

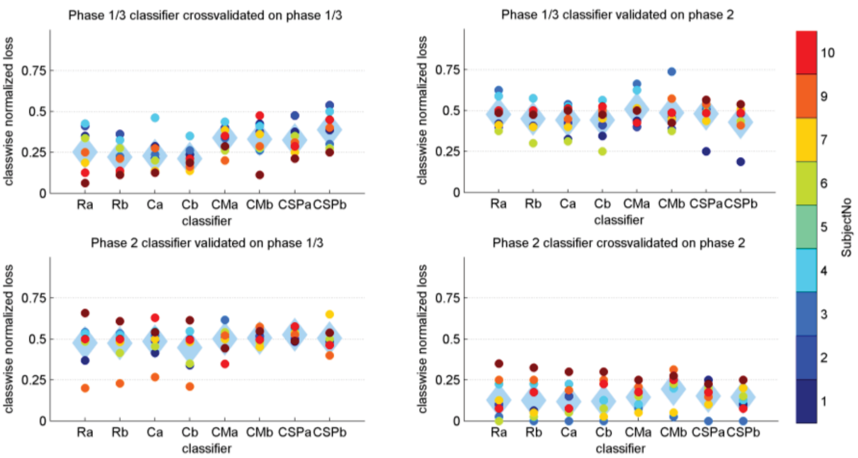

Figure 1. ***Classification matrix for different features:*** ***R** HP(1Hz),* ***C** MARA,* ***CM** manual artifact removal:* ***a*** *1-Hz bins 1-20Hz,* ***b*** *sum α-(8-12Hz) & θ-band (4-7Hz).* ***CSP:*** ***CSPa*** *α & θ-band,* ***CSPb*** *α, β, γ & θ-band. Circles ●: sinlge subject. Diamonds ◆: mean across subjects.*

Discussion: Classification within phases is in general successful while it works least well in phase 1 which we account to the little familiarization with the simulator and equipment settling time. However, classifiers from different experimental settings work at chance level on others, which could be caused by the task differences: n-back is auditory and thus increasing the visual alpha due to the shift of attention, while in the realistic bow-to-bow task there is a variety of stimuli and senses involved. Different subject specific cognitive strategies in the realistic task could additionally lead to the variances of the results as there is more behavioral freedom. Therefore, a general classifier probably has to be based on more than one setting, more data and more subjects.

Significance: A measure of workload can be derived from spectral features of EEG in a complex maritime scenario, but neural patterns differ from a 2-back task - often used in laboratory studies. Online feedback of the workload level to trainer and trainee her/himself is expected to facilitate tugboat and other captains training.

References

[1] WK Kirchner. Age differences in short-term retention of rapidly changing information. *J. Exp. Psychol,* 55(4):352-8, 1958.

[2] C Vidaurre et al. Time domain parameters as a feature for EEG-based brain computer interfaces. *Neural Netw.* 22, 1313–1319, 2009.

[3] I Winkler et al. Automatic classification of artifactual ICA-components for artifact removal in EEG. *Behav. Brain Funct.*, 7:30, 2011.

[4] G Blanchard et al. BCI Competition 2003 - Data Set IIa: Spatial Patterns of Self-Controlled Brain Rhythm Modulations. *IEEE Trans Biomed Eng*, 51(6):1062-1066, 2004.