Using Mobile EEG to Assess Brain Health and Performance

Olave E. Krigolson

Centre for Biomedical Research, University of Victoria

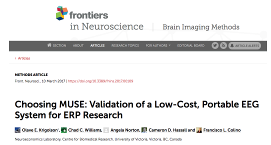
University of Victoria | Theoretical and Applied Neuroscience Laboratory

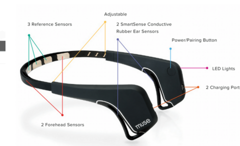
NSERC CRSNG

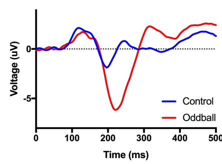
INTRODUCTION

In recent years it has become possible to use mobile electroencephalographic (mEEG) technology to collect research grade data (Krigolson et al., 2017). The recent advances in mEEG data quality and the ease of use have opened the 147 doors for a wide range of real-world applications for human neuroimaging in addition to allowing large scale data collection. Here, we present the results from a large sample size study (n = 1000) wherein we used a combination of event-related potentials (ERPs), time-frequency analysis (FFTs), and machine learning classifiers to examine relationships between neural data and cognitive fatigue. In this study, participants played two simple games on an Apple iPad using PEER research software a visual oddball task and a two-choice gambling task while mEEG data was recorded from a MUSE headband. In line with previous research, our results demonstrate that diminished ERP responses (P300, reward positivity) are associated with increased cognitive fatigue. Further, using a combination of multivariate regression and machine learning classifiers we were able to greatly increase the explained variance in our results (Discriminant Analysis Classifier with Bayesian Optimization, 91.6% accuracy) and come up with a more accurate prediction of cognitive fatigue level. Importantly, we demonstrate two key things here. One, we provide further evidence for the use and validity of mEEG in research. Two, we provide an important building block for cognitive fatigue detection capability something that obviously could have huge impact in a variety of real-world applications.

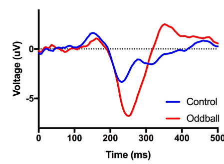
METHODS



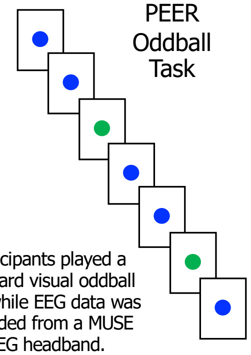




Standard EEG System



MUSE

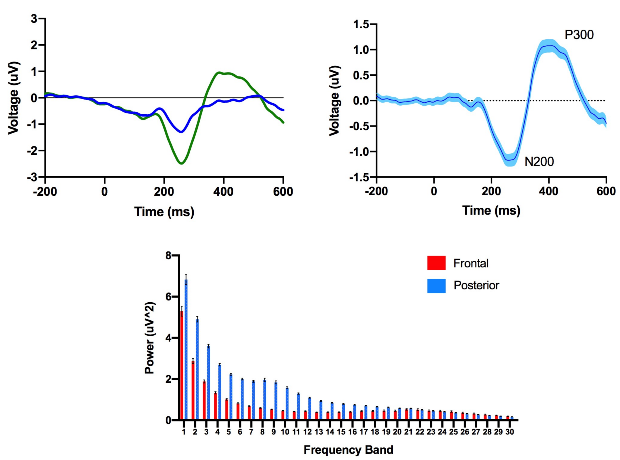


Participants played a standard visual oddball task while EEG data was recorded from a MUSE EEG headband.

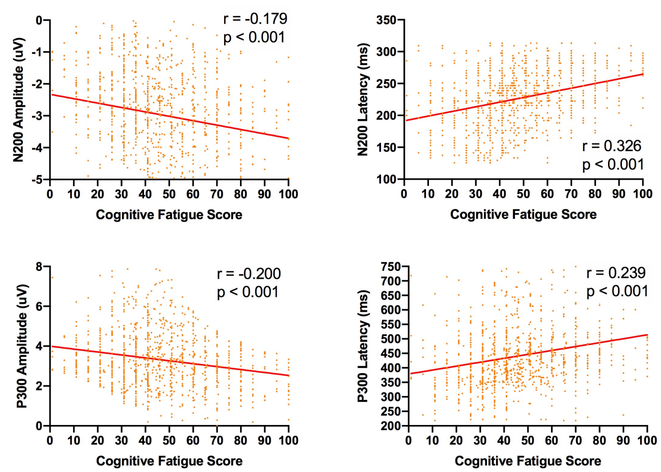
PEER

Portable EEG ERP Researcher

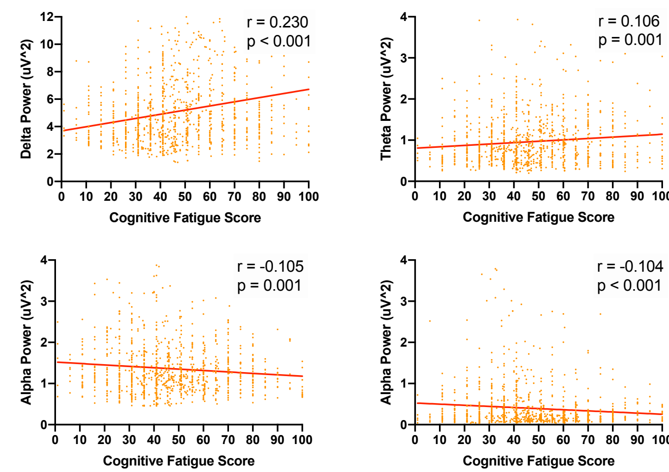
RESULTS



Grand Average ERP waveforms and the associated difference waveform plotted with 95% confidence intervals. Note, this data reflects the pooled average of electrodes TP9 and TP10. Also plotted is the frequency data across performance of the oddball task.



Relationships between the ERP features for the N200 and P300 (amplitude and latency) and perceived cognitive fatigue score.



Relationships between the power in four frequency bandwidths (frontal delta, frontal theta, posterior alpha, and frontal beta) and perceived cognitive fatigue score.

REGRESSION ANALYSIS

We used multiple regression and constructed a model that combined all of the ERP and FFT features to predict perceived cognitive fatigue. Here we found that a model could be constructed that provided a considerably more accurate prediction of perceived cognitive fatigue, **F(7,999) = 49,81; r = 0.510** [Model Components: N200A, frontal delta, P300A, posterior delta, posterior theta, N200A, N200L].

MACHINE LEARNING

We also used machine learning classifiers to attempt to find a more accurate classification of perceived cognitive fatigue. Our input to the classifiers were the ERP and spectral features (e.g., N200 amplitude, frontal theta power) as opposed to the actual trial data (which we feel would be more accurate – this analysis is in progress). In any event, we did find that a **Cubic Support Vector Machine we were able to get a 90.9%** successful classification rate with cross validation.