Camera-based Detection of the Early Stages of Fatigue: Validation with MEG and Self-Assessment Data

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Abstract
The early stages of fatigue are associated with a transient, subconscious decrease in cognitive ability, which can influence decision making. Here, we present a camera-based method that detects the early stages of fatigue. From a 3-hour long experiment conducted on 12 subjects, we acquired synchronous camera (visual) and Magnetoencephalography - MEG (brain) data. We extracted eyelids and head-movement related features and trained Random Forest, K Nearest Neighbor and Support Vector Machine classifiers to distinguish between Non-Fatigue and Fatigue classes, achieving test accuracies of 98%, 97% and 92%, respectively. We then introduced a temporal sliding window method where the percentage of points classified as 'Fatigue' is used as a metric of the gradual change in fatigue levels, leveraging a progressive increment in detection of Fatigue classes as the window slides towards the later stages of the experiment. For validation, we performed regression between our model’s predictions and fatigue-induced alpha band (8-12Hz) power increases in MEG, yielding an average $\rho^2=0.6$. Our results also correlated well with a self-reported behavioral metric. This work describes our ongoing effort to develop a real-time vision-based early-fatigue detection system.

Keywords: Early-Fatigue Detection; Computer Vision; Magnetoencephalography.

Introduction
Cognitive fatigue is defined as the gradual decrease in cognitive performance when performing a mental or physical activity for a long period of time. Behavioral-based studies and relevant technologies have focused on detecting fatigue at its latest stage, when behavioral symptoms are prominent enough to be picked up by the system. However, the ability to visually detect the early stages of fatigue can help prevent numerous workplace hazards where top cognitive performance is of utmost importance. This paper presents our work on finding a gradual progression of fatigue levels using a high speed camera. We extracted 14 visual features to train a classifier and detect the levels of fatigue; We propose a novel method where the percentage of points classified as 'Fatigue' in a sliding window is used as a means to detect early stages of fatigue. Our results are validated in 12 subjects using two different approaches: brain data acquired using magnetoencephalography (MEG) and a commonly used self-reporting behavioral metric. Both validations resulted in high correlation values between our method’s predictions and groundtruth.

Methods
We conducted a 3-hour long experiment on 12 test subjects who played a game that required cognitive efforts. Subjects were recorded through a high-speed camera and an MEG system (Fig. 1A). Using a face tracking system, we obtained 66 face landmark points for each test subject for each frame in the video recording. From these face landmark points, we derived a set of eight eye related features- average eyelid distance, eye closure time, eye blink rate, surface area of the eye, circularity of eye, distance of eye corners from a fixed point, eye opening time and eye closing time. We also derived set of six head movement related features, namely the pitch, yaw and roll velocities and accelerations. The features were extracted in a sliding window of 1 minute.
Figure 1: A: The experimental setup and face tracking. B: Visual indication of level of fatigue over 180 minutes, segmented into six time blocks of 21 minutes length. Blue bars indicate percentage of detection of the Non-Fatigue class and red bars indicate the percentage of detection of the Fatigue class by SVM in that time block. The result is averaged over all 12 subjects. C: For test subject 2, plots for the behavioral metric, Percentage of points classified as Fatigue using our proposed sliding window technique and alpha band power in a window of thirty minutes. D: Correlation coefficient of behavioral and MEG data and fatigue classification for all subjects.

Correlation with "Self-Reported" Fatigue Level
Following a common practice (Faber, Maurits & Lorist, 2012), we asked the subjects to self-report their level of resistance against performing the task (with 1 and 8 indicating no and maximum resistance, respectively) every 30 minutes. We computed Pearson’s correlation coefficient between the behavioral metric, and the percentage of points classified as Fatigue (using our sliding window technique), both normalized between 0 and 1 (Fig. 1D).

Validation using MEG
We estimated the alpha band (8-12 Hz) power in the MEG data, across all sensors and regressed it against the model’s predictions. We obtained an average $\rho^2 = 0.6$.

Conclusion
We propose a novel sliding window technique that employs the percentage of points classified as Fatigue as a proxy for detecting the early stages of fatigue. Our results demonstrate promise in terms of developing a vision-based model to be embedded into a real-time fatigue detection system.

References