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

Neelesh Kumar (neelesh.kumar@rutgers.edu)
Department of Computer Science
Rutgers University, USA

Chintan Trivedi (chintan.trivedi@rutgers.edu)
Department of Computer Science
Rutgers University, USA

Lezi Wang (lw462@cs.rutgers.edu)
Department of Computer Science
Rutgers University, USA

Dimitris N. Metaxas (dnm@cs.rutgers.edu)
Department of Computer Science
Rutgers University, USA

Konstantinos P. Michmizos (konstantinos.michmizos@cs.rutgers.edu)
Department of Computer Science
Rutgers University, USA

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 ρ^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; Magnetoencaphalography.

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.

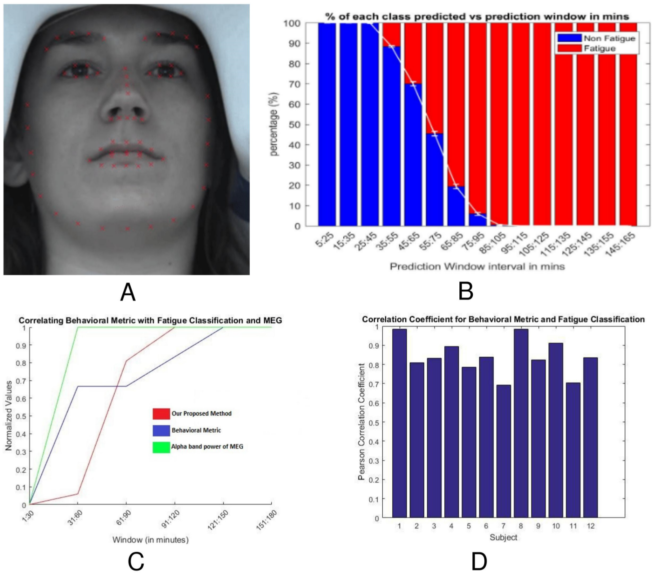

Figure 1: **A:** The experimental setup and face tracking. **B:** Visual indication of level of fatigue over 180 minutes, segmented into six time blocks of 21 minutes length. Blue bars indicate percentage of detection of the Non-Fatigue class and red bars indicate the percentage of detection of the Fatigue 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.

Fatigue Classifiers and Model Fitting

We trained Random Forest, K Nearest Neighbor and Support Vector Machine classifiers to distinguish between Non-Fatigue and Fatigue. The class labels were generated by assuming that subjects were not tired in the first 21 minutes of the experiment ("Non Fatigue") and that they were tired in the final 21 minutes of the experiment ("Fatigue"). We achieved a test accuracy of 98%, 97% and 92% when tested across all subjects.

Detecting the Early Stages of Fatigue

We propose a temporal sliding window technique of using the above binary classifiers to detect a gradual change in the level of fatigue. Specifically, we tested our trained model on a sliding window of 21 minutes, with an overlap of 5 minutes, slid through the duration of the experiment. We observed a progressive increment in detection of Fatigue class, i.e. percentage of points classified as Non-Fatigue is high in the beginning and decreases as we move towards the end of the experiment, with a simultaneous increase in the percentage of points classified as Fatigue (Fig. 1B). We also observed a sharp change in the labels from non-fatigue to fatigue in the interval of 50-60 minutes which signifies early stages of fatigue.

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

Faber, L. G., Maurits, N. M., & Lorist, M. M. (2012). Mental fatigue affects visual selective attention. *PloS one*, *7*(10), e48073.

Klimesch, W., Doppelmayr, M., Russegger, H., Pachinger, T., & Schwaiger, J. (1998). Induced alpha band power changes in the human eeg and attention. *Neuroscience letters*, *244*(2), 73–76.

Sacco, M., & Farrugia, R. A. (2012). Driver fatigue monitoring system using support vector machines. In *Communications control and signal processing (isccsp), 2012 5th international symposium on* (pp. 1–5).

Trejo, L. J., Kubitz, K., Rosipal, R., Kochavi, R. L., & Montgomery, L. D. (2015). Eeg-based estimation and classification of mental fatigue. *Psychology*, *6*(05), 572.

Vigário, R., Sarela, J., Jousmiki, V., Hamalainen, M., & Oja, E. (2000). Independent component approach to the analysis of eeg and meg recordings. *IEEE transactions on biomedical engineering*, *47*(5), 589–593.

Wang, H., Zhou, L., & Ying, Y. (2010). A novel approach for real time eye state detection in fatigue awareness system. In *Robotics automation and mechatronics (ram), 2010 ieee conference on* (pp. 528–532).

Yu, X., Lin, Z., Brandt, J., & Metaxas, D. N. (2014). Consensus of regression for occlusion-robust facial feature localization. In *European conference on computer vision* (pp. 105–118).