EEG-BASED MICROSLEEP DETECTION USING SUPERVISED LEARNING

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INTRODUCTION: Tiredness and fatigue can often lead to brief instances of people falling asleep while engaged in some active task such as driving a motor vehicle. A study on fatigue by the General Association of German Insurance Industries, identified microsleep as the principal cause of 24% of fatal motorway accidents. Performance lapses range from brief pauses to "microsleeps", which are brief, involuntary events of lapses in attention or responsiveness associated with events such as prolonged eye closure, blank stare etc. The aim of this project was to identify reliable physiological cues indicative of lapses, related to behavioural microsleep episodes, from the EEG, which could in turn be used to develop a real-time lapse detection (or better still, prediction) system.

METHODS: 8 normal healthy male volunteers aged 18–36 years (mean = 26.5) performed a visuomotor tracking task while EEG, facial video, and tracking behavior were recorded. EEG was recorded from electrodes at 16 scalp locations and digitized at 256 Hz (bandwidth 0.1–100 Hz) [1]. Models based on EEG power spectral features, such as power in the traditional EEG bands and ratios between those bands, were developed to detect the change of brain state during the microsleeps. Signals from eye movements, blinks, cardiac signals, muscle noise, and, line noise can be in orders of magnitude larger than brain-generated electrical potentials and are one of the main sources of artefacts in EEG data. Hence, each EEG channel was processed by rejecting epochs contaminated with artefacts. Following the removal of eye blink artefacts from the EEG, the signal was transformed into z-scores relative to the baseline of the signal. An epoch length of 2 s and an overlap of 1 s (50%) between successive epochs were used for all signal processing algorithms. Principal component analysis (PCA) and average distance between events and non-events (ADEN) were used to reduce the redundancy in the features extracted across all the EEG derivations. Linear discriminant analysis (LDA), support vector machines (SVM) and echo state networks with leaky integrator neurons (ESN-LIN) were used to form individual classification models capable of detecting lapses using data from all the subjects.

RESULTS: Individual microsleep detection models were formed using each of the classifier modules and subsequently, the results were analysed. The performance measure of the microsleep detection system was calculated in terms of its ability to detect the underlying microsleeps (in 1-s epochs). Best performance in microsleep detection was achieved using the single classifier model of the SVM with mean correlation of $(\varphi) = 0.43 \pm 0.02$, whereas the single classifier module with LDA resulted only in a mean correlation of $(\varphi) = 0.23 \pm 0.04$. However, classifier models with echo state networks with leaky integrator neurons were able to achieve a mean correlation of $(\varphi) = 0.40 \pm 0.03$ in terms of their classification.

DISCUSSION & CONCLUSIONS: Even though the performance of the EEG-based lapse detection system from all the classifier modules investigated was modest at best, there is strong evidence which indicates that using combined classifier modules (ensemble classification) may lead to a better classification rates. Hence, further research is needed to develop classifier modules incorporating several sophisticated ensemble learning techniques which may lead to a state-of-the-art microsleep detection system capable of detecting and/or predicting microsleeps.

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