A Novel Non-Intrusive Approach to Assess Drowsiness Based on Eye Movements and Blinking

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Problem - Sleep loss has reached epidemic proportions. It is estimated that 50-70 million Americans suffer from sleep disorders [1], and on average, we get 20% less sleep than a century ago [2]. Sleep deprivation results in increased drowsiness, fatigue, and cognitive deficits, which can have a negative impact on health, safety and performance [3], and even deadly consequences. Nearly 3% of crash fatalities in 2014 involved drowsy driving on US roadways [4], with more than 80,000 sleep-related crashes each year. Accordingly, development of reliable real-time systems to identify impaired vigilance is crucial for reducing the risk of fatigue-related accidents.

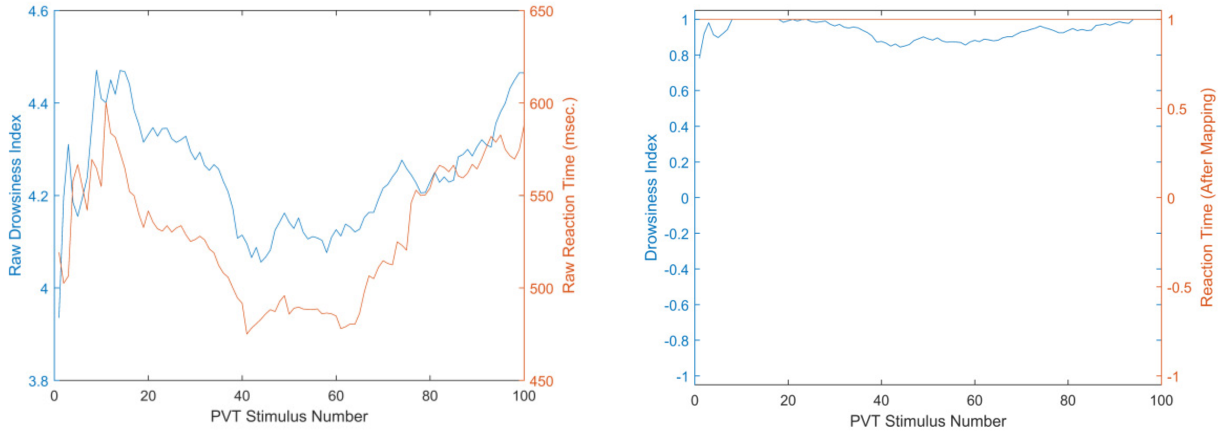
Method - Here, we propose a novel approach to non-intrusively assess drowsiness based on characteristics of eye movements and blinking. The methodology is based on learning a Gaussian mixture model (GMM) [5] of the state of alertness and measuring the distance between the observed state and the reference model. Due to the variation within the alert state, i.e. existence of sub-clusters, a GMM estimator (with a flexible number of components) would be more intuitive. In this study, the reaction times to visual stimuli during a psychomotor vigilance task (PVT) [6] were used as the baseline. The experiment included 6 episodes of 10-min PVT, each consisting of 100 stimuli-response trials. Throughout the experiment, the subject was under surveillance using an infra-red-based eye tracking system continuously acquiring gaze and blink measurements. For each PVT stimulus, we considered a10-second window immediately preceding that stimulus and extracted a set of 25 features (Table 1) from the corresponding eye tracking data (i.e. 600 feature vectors per experiment). Each feature vector was then considered as an observation and linked to the reaction time to the corresponding stimulus. After splitting each subject's data into separate training and test sets, the training observations representing the alertness (based on the corresponding reaction times) were used to build the GMM for each subject. Moreover, dimensionality of the feature vector was reduced to 10 by Fisher's discriminant analysis after estimating a projection matrix using the training set. Finally, given an observation, the minimum Mahalanobis distance logarithm between that observation and centres of GMM components was computed as a raw index and then mapped into [-1,1], using a piece-wise-linear model with saturation, to calculate the *drowsiness index*.

Table 1. List of the extracted features

Gaze SD** in x- and y-coordinates	Fixation duration	Saccade duration	Blinking duration
Gaze median in x- and y-coordinates	Fixation frequency	Saccade frequency	Blinking frequency
Gaze scanpath in x- and y-coordinates	Fixation time percentage	Saccade time percentage	Blinking time percentage
Gaze velocity in x- and y-coordinates	Fixation scanpath in x- and y-coordinates	Saccade scanpath in x- and y-coordinates	
	Fixation velocity in x- and y-coordinates	Saccade velocity in x- and y-coordinates	

** standard deviation

Results - Eye tracking data was acquired using the GazePoint GP3 Eye Tracker from 15 participants (age 22.9±3.3 years; 11 female) at the Brain and Mind Sleep Research Laboratory, Western University, Canada. Each subject participated in two sessions with different sleep requirements: normal sleep (NS) and sleep restriction (SR) sessions, spaced at least 72 hours apart. During the night prior to NS session, the subject was required to have extended sleep for 9 hours (12-9am), while in case of SR session, the sleep was restricted to 5 hours (1:30-6:30am). The subject's compliance with these requirements was verified using a sleep log and actigraphy.



(a) (b)

Figure 1. Drowsiness index and reaction time for a PVT episode from Subject 2 (SR session). **(a)** The raw index and reaction time, and **(b)** the drowsiness index and reaction time (mapped into [-1,1] using a piece-wise-linear model).

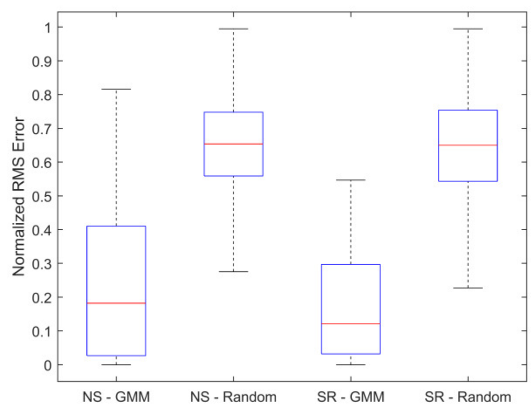


Figure 2. The normalized RMS error between the GMM-based drowsiness index and reaction time (after mapping) for all subjects together. The results are reported for the proposed method for both NS and SR sessions, in comparison to a random estimator.

The method was evaluated on the data acquired from each subject in every session (NS or SR) using a leave-one-out cross-validation approach; i.e., choosing one PVT episode for validation each time and using the remaining episodes for training. For evaluation purpose, the corresponding reaction times were also mapped into [-1,1] using a piece-wise-linear model with saturation. The normalized root-mean-square (RMS) error between the drowsiness index and the corresponding reaction time was then calculated to assess the performance. Furthermore, the performance of the proposed method was compared to a random estimator. Overall, the proposed method shows low normalized RMS errors for both NS and SR sessions, while outperforming the random estimator (Figures 1-2). Taken together, these results suggest a high correspondence between features extracted from eye tracking and reaction time during a sustained vigilance task (as discussed below).

Discussion - As an example at the individual level, Figure 1 depicts the proposed GMM-based drowsiness index and the corresponding reaction times for a PVT episode in an SR session (Subject 2). According to the reaction time values (all greater than 475 ms), the subject can be considered drowsy for the whole episode. As shown in Figure 1(a), the raw drowsiness index correlates well with the reaction time (r = 0.79, p<0.001), while the drowsiness index shows a small deviation (0.04 of RMS error) from the reaction time after mapping (Figure 1(b)). Figure 2 shows the overall performance of the proposed GMM-based methodology for all subjects together (both NS and SR sessions) in comparison to a random estimator. As shown, the median normalized RMS error between the drowsiness index and reaction time is less than 0.2 for both sessions, suggesting high correspondence between the proposed index and the baseline. Moreover, the normalized RMS error for GMM-based method is significantly lower than the random estimator (p<0.001). On the other hand, the RMS error for the NS session is higher than SR (p<0.05), which is expected due to the sleep deprivation effect causing stronger discrimination between the alert and drowsiness states during the SR session. Results of this preliminary study verify the potential of the proposed methodology as a reliable approach for non-intrusive assessment of drowsiness, based on eye movements and blinking. Further investigations, under various levels of fatigue and time of day, will be required to assess the performance of this methodology. Since the reaction time can also be influenced by other factors such as distraction or disengagement, in future studies, we will also utilize biological measures, such as electroencephalogram (EEG) and electrocardiogram (ECG), to have a more reliable baseline for evaluation of the proposed methodology.

Summary - Several methodologies for evaluating human vigilance and fatigue have been developed in the recent past, e.g. for drivers [7]. However, major limitations of these techniques are that they may detect sleepiness too late to effectively prevent fatigue-related accidents, may not be robust under various environmental conditions, can be poorly evaluated, and/or can be intrusive. Here, we present preliminary results for a non-intrusive drowsiness detection technique based on GMM of the alert state which relies on features extracted from eye movements and blinking. The proposed drowsiness index presents high correspondence with reaction times, recorded during a PVT experiment, as the baseline. Importantly, the proposed methodology significantly outperforms a random estimator. Ultimately, this research would lead to development of non-intrusive real-time techniques to reliably assess the state of vigilance, which is critical for managing fatigue in people and reducing motor vehicle collisions and human fatalities.

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