Detection and Prediction of Microsleeps from EEG using Spatio-Temporal Patterns

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***Abstract*— A microsleep is a brief lapse in performance due to an involuntary sleep-related loss of consciousness. These episodes are of particular importance in occupations requiring extended unimpaired visuomotor performance, such as driving. Detection and even prediction of microsleeps has the potential to prevent catastrophic events and fatal accidents. In this study, we examined detection and prediction of microsleeps using EEG data of 8 subjects who performed two 1-h sessions of continuous 1-D tracking. A regularized spatio-temporal filtering and classification (RSTFC) method was used to extract features from 5-s EEG segments. These features were then used to train three different linear classifiers: linear discriminant analysis (LDA), sparse Bayesian learning (SBL), and variational Bayesian logistic regression (VBLR). The performance of microsleep state detection and prediction was evaluated using leave-one-subject-out cross-validation. The detection performance measures were AUC$_{\mathrm{ROC}}$ 0.96, AUC$_{\mathrm{PR}}$ 0.52, and phi 0.47. As expected, prediction of microsleep states with a 0.25-s ahead prediction time resulted in slightly lower performances compared to the detection. Prediction performance measures were substantially higher than those achieved with log-power spectral features, i.e., AUC$_{\mathrm{ROC}}$ 0.95 (cf. 0.90), AUC$_{\mathrm{PR}}$ 0.50 (cf. 0.36), and phi 0.46 (cf. 0.34).**

I. Introduction

Microsleeps are brief and unintentional episodes of sleep-related loss of consciousness [1], [2]. Microsleeps can be up to $15\,\mathrm{s}$ and are commonly accompanied by behavioural cues such as head nodding, slow eye-closure, and droopy eyes [2]. Using a 1-D pseudorandom continuous tracking task, Peiris et al. [2] found an average of 15.2 (0.0–72.0) microsleep events per hour. Poudel et al. [3], using a 2-D continuous tracking task with healthy non-sleep-deprived participants, reported an average microsleep rate of $79\,\mathrm{h}^{-1}$ with a mean duration of $3.3\,\mathrm{s}$. Innes et al. [4] found that sleep deprivation increased the propensity of microsleeps. However, the correlation found between the rate of microsleeps when sleep-deprived and when normally-rested was not significant [4].

A national survey in the United States found that 41% of drivers who participated in this survey had fallen asleep at least once while driving [5]. Another study estimated that 21% of fatal crashes in the United States involved a drowsy driver [6]. A similar study in Australia estimated that fatigue was involved in 16% of fatal crashes [7]. Moreover, Vanlaar et al. [8] found that 14% of participants in a public poll in Ontario admitted falling asleep behind the wheel. In the United States, the overall societal cost of drowsy driving has been estimated as $109 billion per year [9]. These studies indicate that drowsiness, and microsleeps in particular, substantially contribute to car accidents. Prediction and ultimately prevention of microsleep events is therefore important for high-risk occupations that require extended unimpaired visuomotor performance, such as truck drivers, pilots, and air-traffic controllers.

Detection and prediction of microsleeps have been the focus of previous studies. Davidson et al. [10] employed a long-short-term-memory (LSTM) recurrent neural network to detect microsleep states with log-power spectral features, in which they achieved a phi of 0.38 and area under the curve of receiver operating characteristic (AUC$_{\mathrm{ROC}}$) of 0.84. Similarly, Peiris et al. [11] used log-power spectral and nonlinear features (e.g., fractal dimension and approximate entropy) to detect microsleep states. They reported that log-power spectral features achieved their highest detection performance with a phi of 0.39 and AUC$_{\mathrm{ROC}}$ of 0.84. Ayyagari et al. [12] employed an echo-state neural network to detect microsleep states from EEG spectral features and achieved 0.88 and 0.44 for AUC$_{\mathrm{ROC}}$ and phi, respectively. Prediction of microsleep states has also been explored with log-power spectral features [13], [14]. Buriro et al. [15] used interchannel relationships between EEG electrodes to predict microsleep states. Their highest performance for 0.25-s ahead microsleep state prediction was achieved with joint entropy features, which resulted in AUC$_{\mathrm{ROC}}$ of 0.95, AUC$_{\mathrm{PR}}$ of 0.50, and phi of 0.47. Despite this research, the performance of microsleep detection and prediction is still relatively moderate for practical use.

In this study, our aim was to investigate the spatio-temporal EEG patterns in detection and prediction of microsleeps. We expected to achieve an improvement in detection and prediction performance by simultaneously exploiting temporal and spatial patterns of EEG. We used a regularized spatio-temporal filtering and classification (RSTFC)

$*$ This work was supported by the University of Canterbury.

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method [16] to extract features of the EEG, which were then fed to linear classifiers for classification. We evaluated the performance of detection and prediction of microsleeps with a leave-one-subject-out cross-validation. This evaluation method was used to ensure that the estimated performance measures were unbiased.

II. Methodology

A. Data

The data used were from a retrospective study [2] which comprised 15 healthy, normally-rested, and non-sleep-deprived participants. The average night sleep for the night prior to experiment was $7.8 \pm 1.2\,\mathrm{h}$. Participants had no history of a sleep or neurological disorder. Participants were instructed to perform a 1-D continuous preview tracking task and follow a descending pseudorandom wave on the screen to the best of their abilities. Each participant took part in two 1-h sessions. During each session, physiological and behavioural data were recorded. The 16-channel EEG was sampled at $256\,\mathrm{Hz}$ from Fp1, Fp2, F3, F4, F7, F8, C3, C4, O1, O2, P3, P4, T3, T4, T5, and T6, relative to linked-ears, according to the international 10-20 system. Facial video and tracking performance were recorded at 25 frames per second and $60\,\mathrm{Hz}$, respectively and were used to identify microsleeps behaviourally. The ethical approval for the original study was obtained from the Canterbury Ethics Committee.

B. EEG preprocessing

A band-pass filter from 0.5 to $45\,\mathrm{Hz}$ was applied to the EEG data. Artefact subspace reconstruction (ASR) [17] was then applied to 2-min EEG segments with 1-min overlaps to minimize stereotypical artefacts (e.g., eye blinks) with a z-score over 5 [13]. Remaining muscle artefacts were minimized using canonical correlation analysis blind source separation [18]. The data were then re-referenced to the common average of all electrodes and downsampled to $128\,\mathrm{Hz}$.

C. Behavioural gold-standard

Identification of microsleeps was done by combining two independent scores: one from the video ratings and one from the tracking-performance analysis. An expert scored facial video based on a 6-scale rating similar to those of Wierwille and Ellsworth [19], namely alert, distracted, forced eye closure, light drowsy, deep drowsy, and microsleep [2]. Tracking performance, however, was analysed using an automated algorithm to identify coherent and incoherent tracking episodes [13]. Finally, video ratings and tracking-performance analysis were merged into a single gold-standard. In this process, a microsleep episode was defined as a deep drowsy or microsleep video-rating in conjunction with an incoherent and erroneous tracking performance for an episode longer than $0.5\,\mathrm{s}$. A responsive episode, on the other hand, was defined as a coherent tracking for at least $5\,\mathrm{s}$, irrespective of the video rating. The remainder of the gold-standard was considered uncertain and was excluded from further analysis.

D. Feature extraction

We utilized RSTFC [16] to extract spatio-temporal features of EEG. RSTFC is a special form of the common spatial patterns (CSP) family to extract discriminatory EEG features, that can simultaneously optimize temporal and spatial filters to maximize the separability of classes. An advantage of RSTFC is its ability to optimize different temporal filters for each electrode. Additionally, it transforms the optimization of temporal and spatial filters into a classical CSP formulation [20], which can be solved with a generalized eigenvalue decomposition. Let $\mathbf{X} \in \mathcal{R}^{C \times T}$ be a single trial of EEG with C electrodes and T time points. The spatio-temporal filter of $\mathbf{X}$ can be formulated as

$$f\left(\mathbf{X}_c\right) = a_c \sum_{n=0}^{N-1} b_n \mathbf{X}_c^{(n)}, \tag{1}$$

where a_c is the spatial filter's coefficient for channel c, b_n is the n^{th} coefficient of the temporal filter, N is the order of temporal filter, and $\mathbf{X}_c^{(n)}$ is an n-point delayed copy of $\mathbf{X}_c$. To reconstruct classical CSP formulation, Eq. (1) can be rewritten as

$$f\left(\mathbf{X}_c\right) = \sum_{n=0}^{N-1} w_{c,n} \mathbf{X}_c^{n}, \tag{2}$$

where $w_{c,n} = a_c b_n$. Therefore, creating an augmented copy of data with multiple delays simplifies the optimization of the spatio-temporal filters to optimizing the generalized Rayleigh quotient

$$\max_{\mathbf{w}} J(\mathbf{w}) = \frac{\mathbf{w}^\top \mathbf{C}_1 \mathbf{w}}{\mathbf{w}^\top \left(\mathbf{C}_2 + \rho \mathbf{I}\right) \mathbf{w}}, \tag{3}$$

where $\mathbf{C}_1$ and $\mathbf{C}_2$ are the average covariance matrices of augmented epochs corresponding to distinct class labels and ρ is the regularization coefficient. Other types of regularization have also been proposed [16], [21], [22], but this study was restricted to the Tikhonov regularization. Generalized eigenvalue decomposition is then used to find the solution to the generalized Rayleigh quotient [16], [20]. Similar to CSP, the log-powers of spatio-temporally filtered EEG data were used as features.

In this study, we investigated the detection and prediction of microsleep states. The EEG segments were extracted $\tau\,\mathrm{s}$ prior to the gold-standard (as shown in Fig. 1). When $\tau = 0\,\mathrm{s}$, the system performs microsleep detection, whereas higher values of τ corresponds to microsleep prediction. We varied τ from 0 to $1\,\mathrm{s}$ to evaluate the performance of system for both detection and prediction with various prediction times. A window size of $5\,\mathrm{s}$ was used for EEG segments, since this had shown good performances in our previous works [13], [15], [23]. The parameter corresponding to the number of delays for the temporal filter of RSTFC was fixed to 32, which resulted in $0.25\,\mathrm{s}$ data augmentation for EEG segments. It should be noted that this value was chosen arbitrarily, but one can perform a cross-validation to identify the optimum value of this parameter. Similar to our previous work [15], the first $2\,\mathrm{min}$ of each session was used as a baseline for features of that session.

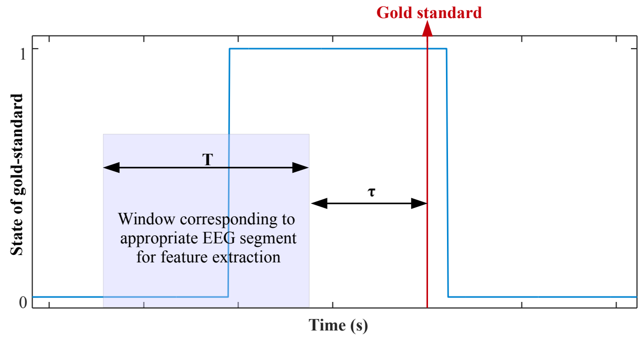

Fig. 1. Assignment of EEG segments with respect to the gold-standard.

E. Classification and performance evaluation

Three linear classifiers were used for identification of micorsleep states: (1) linear discriminant analysis (LDA), (2) sparse Bayesian learning (SBL) – also known as relevance vector machine – [24], [25], and (3) variational Bayesian logistic regression (VBLR) [26]. The LDA is a relatively simple and robust linear classifier which assumes data of each class is generated from a Gaussian distribution [27]. Although a simple classifier, LDA has shown comparable and even superior performance compared to other classification techniques [27], [28]. The SBL method is a hierarchical Bayesian linear classifier with automatic relevance determination (ARD), where each predictor is regularized by a Gaussian prior (L_2 norm). Therefore, irrelevant features prune out automatically during the training of SBL. Bayesian logistic regression also uses ARD to eliminate irrelevant features, while learning to discriminate two classes. Variational inference [26] was used for training of both SBL and Bayesian logistic regression.

To evaluate performance of detection and prediction systems, a leave-one-subject-out cross-validation was performed. First, the data of one subject were kept separate for testing. The data from other subjects were then concatenated to form a training dataset. Spatio-temporal filters of RSTFC were then estimated from the training data, which were then applied to the test data. This process was repeated until all subjects were used for testing. Various performances measures, including $\mathrm{AUC_{ROC}}$, AUC of the precision recall ($\mathrm{AUC_{PR}}$), phi coefficient, geometric mean, sensitivity, and precision were recorded for each subject. The average of each performance measure is reported in this study.

III. Results

We included the data from the 8 participants who had at least one microsleep in the two 1-h sessions. Table I shows various performance measures of microsleep detection across different classifiers. Interestingly, LDA and SBL performed similarly. However, VBLR showed a slightly inferior performance. Since LDA and SBL had similar performance measures, the performance of microsleep prediction is only reported for the SBL classifier (Table II). As expected, the detection performance was higher than for prediction.

TABLE I

Performance of microsleep detection ($\tau = 0$ s) across different classifiers.

	LDA	**SBL**	**VBLR**
$\mathrm{AUC_{ROC}}$	0.96	0.96	0.93
$\mathrm{AUC_{PR}}$	0.52	0.52	0.48
Phi	0.47	0.48	0.43
GM	0.80	0.80	0.76
Sensitivity	0.70	0.69	0.65
Precision	0.43	0.43	0.40

TABLE II

Performance of microsleep prediction for $\tau = 0$ to 1 s with SBL classifier.

	Prediction time τ (s)			
	0.25	0.50	0.75	1.00
$\mathrm{AUC_{ROC}}$	0.95	0.95	0.94	0.94
$\mathrm{AUC_{PR}}$	0.50	0.47	0.44	0.42
Phi	0.46	0.45	0.43	0.41
GM	0.79	0.78	0.76	0.76
Sensitivity	0.67	0.66	0.64	0.63
Precision	0.43	0.41	0.40	0.38

Likewise, increasing the prediction time resulted in lower performances. The drop in performance was more rapid for $\mathrm{AUC_{PR}}$ and phi, which have been shown to be more sensitive to highly imbalanced data [29].

IV. Discussion

Compared to our previous work with power spectral features [13], [14], we found performance improvements. With 0.25-s ahead prediction, the average $\mathrm{AUC_{ROC}}$, $\mathrm{AUC_{PR}}$, and phi increased from 0.90, 0.36, and 0.34 [14] to 0.95, 0.50, and 0.46, respectively. Sensitivity of our system was lower than the previous work, i.e., 0.67 vs 0.72, whereas precision was higher, i.e., 0.43 vs 0.36. Our system, however, performed relatively similar to the one with joint entropy features [15] with similar $\mathrm{AUC_{ROC}}$ and $\mathrm{AUC_{PR}}$, but had slightly lower phi and sensitivity, i.e., 0.46 vs 0.47 and 0.67 vs 0.73, respectively. Increasing prediction time from 0.25 to 1.0 s resulted in a drop of $\mathrm{AUC_{PR}}$ from 0.50 to 0.42 and a deterioration of phi from 0.46 to 0.41. The same trend was also observed in precision with a drop from 0.43 to 0.38 for prediction of 0.25-s and 1.0-s ahead, respectively. The decline in precision may indicate a direct association between prediction time and false positives, where longer prediction time resulted in higher false positives. Although improvements in performances were achieved compared to those studies with log-power spectral features, the detection and prediction performances remain too low for real-life applications.

The results of this study shows that incorporating spatio-temporal information of EEG while extracting features has the potential to substantially improve classification performance. Additionally, increasing the length of temporal filter of RSTFC may increase the accuracy of the temporal filter, hence improve prediction performance. However, increasing the size of temporal filter will lead to more parameters to tune and a larger feature space. Therefore, incorporating L_1 regularization and greedy solutions to RSTFC will be necessary to avoid overfitting.

V. Conclusion

Continuous detection and prediction up to $1\,\mathrm{s}$ of microsleep states were investigated. RSTFC was used to simultaneously optimize spatio-temporal filters for feature extraction. EEG features were extracted from 5-s segments and the size of temporal filter was set to 32. The first two minutes of each session was used as a baseline to correct that session's features. The classification task was done using three linear classifiers: LDA, SBL, and VBLR. The performance of detection and prediction was evaluated based on leave-one-subject-out and the average performances were reported.

Microsleep state detection and prediction with log-power features of spatio-temporally filtered EEG resulted in higher performances compared to those achieved with classical log-power spectral features. This suggests that incorporating spatial and temporal information of EEG during feature extraction can improve classification performance. Despite this improvement, the achieved performances were relatively similar to the ones obtained with joint entropy features. Fine-tuning the order of RSTFC's temporal filter, the length of EEG segment, and regularization parameters can improve the detection and prediction performance of microsleeps.

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