Exploring the EEG Correlates of Neurocognitive Lapse with Robust Principal Component Analysis

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Abstract. Recent developments of brain-computer interfaces (BCIs) for driving lapse detection based on electroencephalogram (EEG) have made much progress. This study aims to leverage these new developments and explore the use of robust principal component analysis (RPCA) to extract informative EEG features associated with neurocognitive lapses. Study results showed that the RPCA decomposition could separate lapse-related EEG dynamics from the task-irrelevant spontaneous background activity, leading to more robust neural correlates of neurocognitive lapse as compared to the original EEG signals. This study will shed light on the development of a robust lapse-detection BCI system in real-world environments.

Keywords: EEG · BCI · RPCA · Drowsiness · Lapse · Driving · Fatigue

1 Introduction

The neurocognitive lapse has been known as a critical safety issue in vehicle driving. Such momentary lapse causes approximate 1.9 million drivers to fatal car accidents with injury or death [1]. Technologies that enable instant lapse detection and feedback delivery to rectify drivers from the occurrence of lapse are thus urgently required. For the past two decades, the noninvasive brain-sensing technology, namely electroencephalogram (EEG), has been adopted for this purpose because of its high temporal resolution of brain signals allowing a prompt response to a neurocognitive lapse. For example, studies have shown strong EEG correlates of behavioral lapses, including power spectra [2–6] and autoregressive features [7, 8]. These EEG features could then be used to develop various on-line/off-line neuroergonomic systems for monitoring drowsiness, fatigue, and behavioral lapse in task performance [2, 3, 9–12]. It is believed that an effective computational approach that can further leverage EEG correlates of neurocognitive lapse is a crucial step for improving the practicability of BCI-based lapse detection system in real life, which is the main focus of this study.

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Robust principal component analysis (RPCA) [13] has recently been shown to be able to separate task-relevant and sparse EEG dynamics from the spontaneous task-irrelevant background activity [14]. The study demonstrated that the RPCA could improve the characterization of emotion-related EEG patterns across different recording days, and in turn facilitate a more effective emotion-classification model. As such, the task-related EEG dynamics of interest could be extracted from the task-irrelevant spontaneous background activity using RPCA, and could alleviate the EEG variability across sessions [14]. Analogously, this study explores the applicability of the RPCA for assessing the EEG correlates of neurocognitive lapses during driving.

2 Materials and Methods

2.1 Experiment and EEG Recording

This proof-of-concept study employed an EEG dataset of eight subjects participating in a lane-keeping driving task (LKT) in which EEG data and human driving behavior were simultaneously recorded [15]. The experiments were conducted in a virtual-reality-based driving simulator. Each subject drove on a straight highway scene during the night with artificial lane-deviation events introduced every 6–10 s. In each lane-deviation event, the car would randomly drift toward to left or right, and the subject was instructed to steer the car back to the cruising position as soon as possible. The duration from the onset of lane-deviant to the onset of steering movement was defined as the reaction time (RT), which indexed the extent of neurocognitive lapse. Longer RT indicated poor driving performance at the given moment. The experiment started in early afternoon when afternoon slump often occurred and thus maximized the opportunity of collecting neurocognitive lapses. The entire session of LKT lasted about 90 min, which was long enough to collect sufficient data under both alertness and drowsiness.

The EEG data were recorded by a 32-channel Quik-Cap electrode system (Compumedics Neuroscan, Inc.). Thirty Ag/AgCl electrodes were deployed according to the modified international 10–20 system, and two reference electrodes were placed upon left and right mastoids. The EEG signals were sampled with 16-bit quantization and 500 Hz sampling rate.

2.2 Lapse Assessment

In this study, a lapse refers to momentary unresponsiveness to the lane-deviation event in the LKT, and its level was quantitatively estimated based on RT. This study empirically defined the RT as alertness if its value was below the 5th percentile of the RTs across entire session for each session. In order to calibrate the individual differences in the distributions of RT values, the RTs of each individual was further normalized into a range of 0 to 1, defined as follows [11, 12]:

$$LI = \max(0, (1 - e^{-(\tau-\tau_0)})/(1 + e^{-(\tau-\tau_0)})) \quad (1)$$

where LI is the normalized lapse index, τ is the RT for a lane-deviant event, and τ_0 is the RT of alert trials. That is, the higher LI value is, the more momentary lapse a subject is. This study used correlation analysis to investigate the relationship between the EEG dynamics and the changes of RT.

2.3 EEG Data Processing

The 30-channel EEG signals referenced to the arithmetic average of left and right mastoid were first submitted to a band-pass finite impulse response filter (2 to 30 Hz) to eliminate DC drift and high-frequency noise including 60 Hz powerline noise. Trials contaminated by artifacts or noise were manually inspected and removed. Next, the filtered 30-channel EEG data were down-sampled to 250 Hz for analysis.

Previous studies [2, 3] have reported significant EEG spectral correlates of RT in stereotype frequency bands, such as delta (2–5 Hz), theta (5–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands. This study thus examined the impact of RPCA processing on EEG spectral time series in the same EEG frequency bands. To assess the associations between EEG dynamics and cognitive lapses, this study first calculated the band power (logarithmic signal variance) of each channel within a 3-s window before the onsets of each lane-deviation events, and then correlated that with the corresponding RT values.

2.4 Robust Principal Component Analysis

The applicability of the RPCA [8] has been demonstrated in effectively separating emotion-relevant and sparse EEG dynamics from the spontaneous task-irrelevant background activity [9]. This study employed RPCA for assessing the EEG correlates of neurocognitive lapses during driving. The RPCA mathematically decomposes multi-channel EEG signals, $X \in R^{m \times n}$ (m: number of attributes, n: number of observations), into a sparse matrix, S, and a low-rank matrix, L, followed by $X = S + L$, which can be efficiently solved by a tractable convex optimization proposed in [13]:

$$\min_{S^+, L^+} \lambda \|S^+\|_1 + \|L^+\|_* \quad \text{subject to } X = S + L \quad (2)$$

where $\|\cdot\|_*$ denotes the matrix nuclear norm, *i.e.*, the sum of singular values, $\|\cdot\|_1$ denotes the L1 norm, *i.e.*, the sum of absolute values of matrix entries, S^+ is the optimized estimate of sparse component, L^+ is the optimized estimate of low-rank component, and λ is a positive regularizing parameter empirically defined as $\lambda = 1/\sqrt{max(m,n)}$ [13]. This study formed the input matrix (m: number of electrodes × number of time points in a 3-s epoch, n: number of epochs in a session) for each subject. The method of augmented Lagrange multipliers [16] was adopted to perform RPCA decomposition. After the RPCA decomposition, the correlation coefficients between the normalized RTs (the lapse index) and the EEG spectral features

estimated separately from the original band-passed EEG signals, sparse component, and low-rank component were compared using a statistical assessment of Wilcoxon signed-rank test. This study hypothesized that the sparse components, S, would profitably extract lapse-related EEG dynamics, and therefore would be more correlated with the RTs, compared to the low-rank components, L, and the original EEG signals, X.

3 Results and Discussion

Figure 1 illustrates the time series of RT profiles before and after the proposed RT normalization in two representative subjects. The alert RT is set to 0.6 s to map the RT to the lapse index. When a RT value is close to the defined alert RT, the lapse index increases more linearly as RT increases, until it reaches to a plateau close to 1 as RT is 4 s or longer. This warping is based on an assumption that there is very little difference in the brain state between 4- and 10-second RT as the subject was unresponsive to lane-deviation events. As can be seen, before the RT normalization shown in Fig. 1(b), S1 seemed to retain alert across the entire session, while S2 frequently behaved with lapse after 10 min driving. However, the lapse index after the RT normalization exhibited realistic fluctuations of lapses for both S1 and S2 in a 90-min driving task as shown in Fig. 1(c).

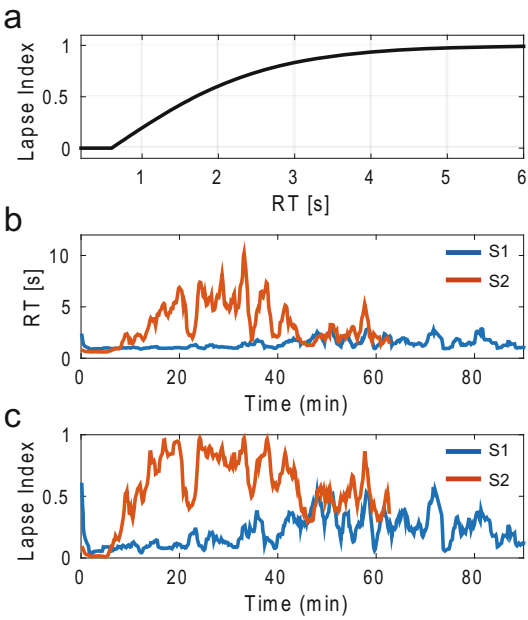

Fig. 1. Time series of RTs before and after RT normalization in two representative subjects. (a) the conversion from RT to the proposed lapse index with alert RT = 0.6 s. (b) the time series of original RTs in Subjects S1 and S2, and (c) the time series of the lapse index after RT normalization.

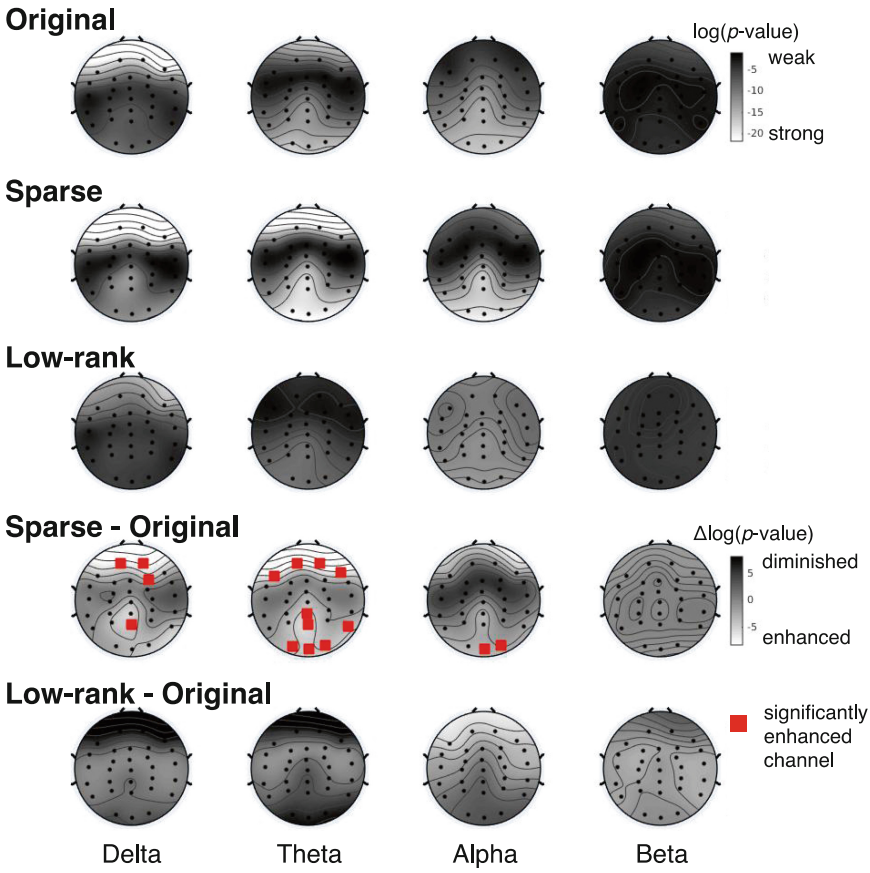

Fig. 2. The statistical significance of the correlations (log p-value) between RTs and band power using (from the top) the band-passed EEG signals (original), sparse components, and low-rank components at different scalp locations. The correlation intensity was estimated by logarithmic p-value from correlation analysis. Brightness in the gray-scaled topographies represents a strong correlation between the EEG band power and RTs. (the 4th row) Sparse - Original (the 5th row, Low-rank - Original) compares the significance of correlations between sparse (low-rank) and the original spectra. The red squares mark the channels with not only strong correlation (log(p) < -11), but also significant increases from that of original EEG band power ($p < 0.05$). (Color figure online)

Figure 2 explores the statistical significance of the correlations (log p-value) between RTs and band power at different scalp locations using the (the 1st row) band-passed EEG signals, (the 2nd row) sparse components, and (the 3rd row) low-rank components. Brightness in gray-scaled topographies represents the correlation was statistically significant (a strong correlation) between the band power and RTs. The 4th (5th) row plots the differences of p-values between the 1st and the 2nd (3rd) rows. The red squares mark the channels whose correlations between the band power and RTs were significantly enhanced in terms of the p-value over using the original EEG band

power. Specifically, the 'Original' scalp map exhibited strong correlations in frontal delta, moderate correlations in frontal theta, and parietal-occipital theta and alpha, which were somewhat in line with previous studies [2–4]. The sparse components obtained by RPCA enhanced the extents of the correlations between the EEG power and RTs at several channels (marked in red), compared to the original scalp-EEG band power. The augmentations in the highlighted channels (see the 4th raw, Sparse - Original) were statistically significant. In contrast, the low-rank component did not provide any improvement in the correlations between EEG power and RTs (see the bottom row, Low-rank – Original).

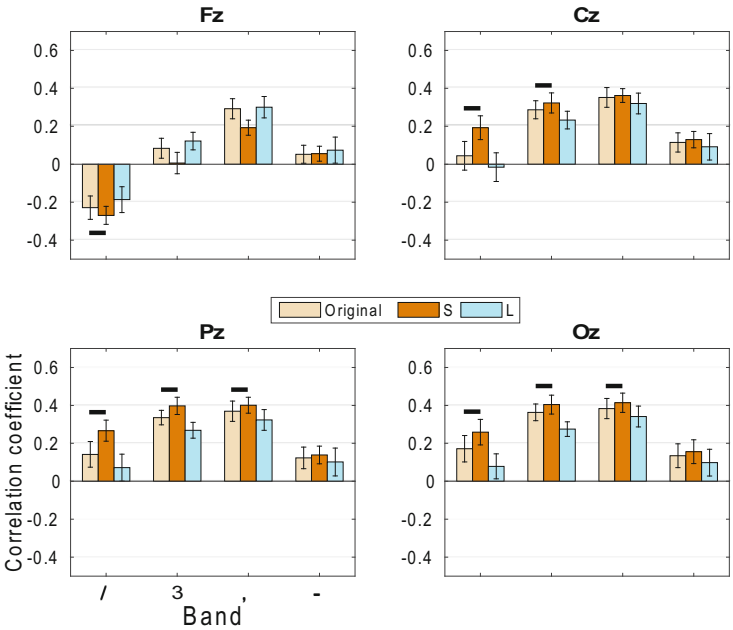

Fig. 3. The average correlation coefficients between band power and RTs at four representative scalp locations (Fz, Cz, Pz, and Oz) using the band-passed EEG signals (Original), sparse components (S), and low-rank components (L). Black bars indicate significant increase (either positive or negative) in correlation coefficient ($p < 0.05$) comparing S to Original.

Figure 3 plots the comparative correlation coefficients between band power and RTs using the band-passed EEG signals, sparse components, and low-rank components at four representative locations, including Fz, Cz, Pz, and Oz. The improvements of spectrum-RT correlation could be found by the enhancement in correlation coefficients between RTs and Fz delta, Cz delta and theta, Pz delta, theta, and alpha, and Oz delta, theta, and alpha power. In particular, the highest correlation could be obtained at Oz (alpha power) using the original band-passed EEG signal, where the sparse component further strengthened this correlation. Subtle discrepancy in statistical testing results could be found as compared to Fig. 2 due to the different measurements (logarithmic

p-values and correlation coefficients) that were used in the statistical test. For instance, there is significant enhancement at F4 delta (see the red dot at delta, 1st column & 4th row in Fig. 2), but no significance at the nearby Fz delta. However, the correlation coefficient was significantly enhanced at Fz delta (see the top left of Fig. 3). Note that the sparse components generated features with higher correlations for most of the comparative conditions, which was consistent with the inference from the results shown in Fig. 2. The comparison of correlation coefficients suggests that sparse component can enhance the discriminative power of lapse-related EEG features.

The above findings evidently proved the posed hypothesis that the sparse EEG signals obtained by RPCA can profitably extract lapse-related EEG dynamics, and therefore carry more informative EEG spectral features accounting for behavioral lapses. In this preliminary proof-of-concept study, with such an improvement in feature extraction for EEG correlates of lapse, we believe that RPCA could boost the performance of a lapse detecting system.

While previous studies have applied independent component analysis (ICA) to extract highly informative EEG correlates of drowsiness [2, 9], a quantitative comparison between RPCA, ICA, and other related approaches on enhancing the quality of EEG features would be of interest to the researchers in this field and a natural next step of this study. Future work will also study to what extent the RPCA-enhanced EEG spectral correlates of neurocognitive lapse can improve the performance of lapse detection, which will increase the practicability of BCI-based lapse detection system in real life.

4 Conclusion

The present study empirically demonstrated the efficacy of RPCA for enhancing EEG correlates of neurocognitive lapse. Study results suggested that the RPCA could be used as a pre-processing step to extract the lapse-related EEG dynamics of interest from the spontaneous background activity, leading to a more robust lapse-detection BCI in real-world environments.

References

1. US National Sleep Foundation: 1.9 Million drivers have fatigue-related car crashes or near misses each year (2009). http://www.sleepfoundation.org/article/press-re-lease/19-million-drivers-have-fatigue-related-car-crashes-or-near-misses-each-year
2. Jung, T.P., Makeig, S., Stensmo, M., Sejnowski, T.J.: Estimating alertness from the EEG power spectrum. IEEE Trans. Biomed. Eng. **44**, 60–69 (1997)
3. Lin, C.-T., Wu, R.-C., Liang, S.-F., Chao, W.-H., Chen, Y.-J., Jung, T.-P.: EEG-based drowsiness estimation for safety driving using independent component analysis. IEEE Trans. Circuits Syst. I: Regul. Pap. **52**, 2726–2738 (2005)
4. Lal, S.K., Craig, A., Boord, P., Kirkup, L., Nguyen, H.: Development of an algorithm for an EEG-based driver fatigue countermeasure. J. Saf. Res. **34**, 321–328 (2003)

5. Peiris, M.T.R., Jones, R.D., Davidson, P.R., Carroll, G.J., Bones, P.J.: Frequent lapses of responsiveness during an extended visuomotor tracking task in non-sleep-deprived subjects. J. Sleep Res. **15**, 291–300 (2006)
6. Davidson, P.R., Jones, R.D., Peiris, M., Davidson, T.R.: EEG-based lapse detection with high temporal resolution. IEEE Trans. Biomed. Eng. **54**, 832–839 (2007)
7. Rosipal, R., et al.: EEG-Based Drivers' drowsiness monitoring using a hierarchical gaussian mixture model. In: Schmorrow, D.D., Reeves, L.M. (eds.) HCII 2007 and FAC 2007. LNCS (LNAI), vol. 4565, pp. 294–303. Springer, Heidelberg (2007)
8. Zhao, C., Zheng, C., Zhao, M., Tu, Y., Liu, J.: Multivariate autoregressive models and kernel learning algorithms for classifying driving mental fatigue based on electroencephalographic. Expert Syst. Appl. **38**, 1859–1865 (2011)
9. Chuang, C.-H., Lai, P.-C., Ko, L.-W., Kuo, B.-C., Lin, C.-T.: Driver's cognitive state classification toward brain computer interface via using a generalized and supervised technology. In: The 2010 International Joint Conference on Neural Networks (IJCNN), pp. 1–7 (2010)
10. Wang, Y.-T., Huang, K.-C., Wei, C.-S., Huang, T.-Y., Ko, L.-W., Lin, C.-T., Cheng, C.-K., Jung, T.-P.: Developing an EEG-based on-line closed-loop lapse detection and mitigation system. Front Neurosci. **8**, 321 (2014)
11. Wei, C.-S., Wang, Y.-T., Lin, C.-T., Jung, T.-P.: Toward non-hair-bearing brain-computer interfaces for neurocognitive lapse detection. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 6638–6641 (2015)
12. Wei, C.-S., Lin, Y.-P., Bigdely-Shamlo, N., Wang, Y.-T., Lin, C.-T., Jung, T.-P.: Selective transfer learning for EEG-based drowsiness detection. In: 2015 IEEE International Conference on System, Man, and Cybernetics (SMC 2015), Hong Kong (2015)
13. Candès, E.J., Li, X., Ma, Y., Wright, J.: Robust principal component analysis? J. ACM. **58**, 11:1–11:37 (2011)
14. Jao, P.-K., Lin, Y.-P., Yang, Y.-H., Jung, T.-P.: Using robust principal component analysis to alleviate day-to-day variability in EEG based emotion classification. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 570–573 (2015)
15. Huang, R.-S., Jung, T.-P., Delorme, A., Makeig, S.: Tonic and phasic electroencephalographic dynamics during continuous compensatory tracking. NeuroImage. **39**, 1896–1909 (2008)
16. Lin, Z., Ganesh, A., Wright, J., Wu, L., Ma, Y.: Fast convex optimization algorithms for exact recovery of a corrupted low-rank matrix. In: Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP) (2009)