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UMM: Unsupervised Classification of ERPs with Confidence

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Introduction: Attended and unattended stimuli differ in the shape, amplitude and latency of the transient amplitude responses they leave in a user's brain activity. Evoked by visual, haptic or auditory stimuli, measured by magneto- or electroencephalography (MEG, EEG) and classified into attended or unattended stimulus events by machine learning methods, event-related potential (ERP) BCIs provide spelling applications or allow user interfaces to determine a desired control command. While shrinkage linear discriminant analysis (sLDA) is a widespread method for supervised classification that recently has undergone further improvements using a Toeplitz structure of the covariance [1], lately also classifiers leveraging Riemannian geometry and even neural network approaches have been investigated for ERP data in BCIs. In addition, unsupervised approaches based on learning from label proportions show promising results, however, they require a substantial warm-up period but no labeled calibration data [2]. In this work, we go one step forward by proposing **unsupervised mean-difference maximization (UMM)**, a novel classification method for ERP protocols.

Material, Methods and Results: UMM generally uses data merely from the current trial. For every available symbol $s \in S$ we can construct the *hypothesis* that s had been the attended symbol and obtain a corresponding target assignment containing all epochs of the current trial where s was highlighted, and analogously the non-target assignment. For every hypothesis s, the distance vector $\Delta\mu_s$ between the corresponding hypothetical class means is obtained. To take into account high-dimensional and noisy data, UMM employs the squared Mahalanobis distance $d^{\Sigma}(s) = (\Delta\mu_s)\Sigma^{-1}(\Delta\mu_s)^{T}$, which removes the influence of correlated dimensions by using the inverted global covariance matrix Σ^{-1}. The attended symbol can then be determined by $s^{*} = \text{argmax}\ d^{\Sigma}(s)$. As in LDA classifiers [1], we found a benefit in using a block-Toeplitz regularization of the covariance estimate in UMM. Comparing the distances of the winning assignment and the runner-up, UMM also provides a confidence metric for its decision. We tested UMM on three visual ERP speller datasets [3] representing 12 (Huebner2017), 13 (Huebner2018) and 54 (Lee2019, 108 sessions) healthy participants. It delivered competitive letter selection accuracy of 92%, 96% and 74%, outperforming the original unsupervised results (Huebner2017, Huebner2018), which is considerable given UMM does not learn over time and never sees more than 68 epochs.

Discussion: UMM is simple, yet effective. Being unsupervised, it neither requires recording labelled nor unlabeled calibration data. As it acts instantaneously on the ERP epochs of the current trial, UMM is immune to non-stationary feature changes over an EEG session. Compared to other unsupervised methods, it can be used for virtually any ERP protocol without requiring changes to the experimental protocol or interface. The proposed instantaneous version of UMM can easily be expanded to consider a history of previous data to obtain improved covariance and mean estimates, which may be useful for more challenging ERP data from patients or auditory protocols.

Significance: Practitioners may want to consider incorporating UMM into their BCI systems to eliminate the need for calibration and to allow participants to instantly use their ERP-BCI application.

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References

[1] Sosulski J. and Tangermann M. (2022). Introducing block-Toeplitz covariance matrices to remaster linear discriminant analysis for event-related potential brain–computer interfaces. *J. Neural Eng.* 19 066001. **DOI 10.1088/1741-2552/ac9c98**.
[2] Hüebner, D. et al. (2018). Unsupervised learning for brain-computer interfaces based on event-related potentials: Review and online comparison. *IEEE Computational Intelligence Magazine*, *13*(2), 66-77. **DOI 10.1109/MCI.2018.2807039**
[3] Jayaram V. and Barachant A. (2018). MOABB: trustworthy algorithm benchmarking for BCIs. J. Neural Eng., vol. 15, no. 6, p. 066011. **DOI 10.1088/1741-2552/aadea0**.