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BCI-sift: An Automated Feature Selection Toolbox for Brain-Computer Interface Applications

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Introduction: Advancements in Brain-Computer Interfaces (BCIs) for clinical applications rely on precise and reliable signal interpretation. However, the high-dimensional and noisy nature of data captured from both implanted and non-implanted BCIs presents significant challenges, necessitating the use of sophisticated filtering techniques, such as feature selection algorithms. We introduce the Python-based BCI-sift (BCI Systematic and Interpretable Feature Tuning) Toolbox, a comprehensive tool designed to streamline the application of diverse machine-learning algorithms to BCI datasets for identifying the most relevant features in classification tasks. By enhancing classification accuracy, inference speed, and interpretability, BCI-sift addresses key challenges in developing efficient and transparent BCI systems.

Material, Methods and Results: Our scikit-learn-compatible toolbox (github.com/UMCU-RIBS/BCI-sift) simplifies feature selection in classification tasks by integrating advanced machine learning methods, including stochastic hill climbing, simulated annealing, evolutionary algorithms, recursive feature elimination, and particle swarm optimization. These techniques optimize classification performance on cross-validated training sets, with reported accuracies reflecting the application of identified optimal features to held-out test data.

We validated the toolbox using a dataset of eight able-bodied participants with 64 to 128 implanted high-density electrocorticography (ECoG) electrodes (1-mm exposed diameter, 3- or 4-mm inter-electrode distance). The electrodes were placed on the sensorimotor cortex (SMC), and participants repeatedly spoke 12 different words. BCI-sift effectively identified informative neural features across time points, channels, and frequency bands.

In the channel dimension, BCI-sift identified an optimal number and location of channels associated with highest classification accuracy. These selections were consistent across participants and aligned with the functional and anatomical organization of motor activity in the SMC. In the time dimension, the most relevant time points were clustered around word pronunciation on- and offsets. In the frequency dimension, when selecting from delta [0,5 – 3 Hz], theta [4 – 7 Hz], alpha [8 – 12 Hz], beta [13 – 30 Hz], and the high frequency band (HFB) [70 – 170 Hz], BCI-sift identified HFB as most informative for classification, consistent with prior research.

Beyond providing interpretability, BCI-sift significantly improved classification accuracy compared to using no feature selection. For instance, the classification accuracy of 12 different spoken words across eight participants increased from 26±10% to 75±22% ($p = 0.008$, Wilcoxon signed-rank test) with the best-performing optimization algorithm (recursive feature elimination) on the frequency band dimension, driven by the removal of noisy features. BCI-sift selects optimally performing classification features automatically from multi-dimensional input brain data. It outputs informative plots and tables for interpreting results.

Conclusion: With BCI-sift, we provide an accessible and versatile platform for feature selection in BCI research, enabling improved classification accuracy, automatic feature analysis, and enhanced interpretability. Although we validated BCI-sift with ECoG data, the underlying principles are equally applicable to other implanted recording modalities as well as non-implanted BCI data. We encourage researchers to explore and apply BCI-sift in these contexts as well.

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