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Contrastive Self-Supervised Learning for Motor Imagery: impact of the embedding size

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Introduction: Due to the intra- and inter-individual variability of the electroencephalography (EEG) signals, brain-computer interfaces (BCI) require a daily user-specific calibration. This offline calibration step is necessary to set feature extraction, classification and pre-processing parameters. Yet, it is time consuming and might cause fatigue before the actual use of the BCI. Our goal is to reduce this time with a self-supervised classification method that achieves good detections with minimal calibration trials, for use in a motor imagery (MI)-based BCI that aims to enhance the rehabilitation of stroke patients. To process a small amount of labeled data, self-supervised learning (SSL) is currently the state-of-the-art method in the fields of vision and natural language processing [1], which makes it interesting to explore for EEG data.

Material, Methods and Results: Dataset 2a of the BCI competition IV [2] was used to estimate the capability of contrastive SSL (CSSL). Two sessions of 72 trials each are available for training and testing. The classifier has to detect a right (or left) hand MI relative to a resting period. CSSL uses a pretext task (PT) to create sample pairs from unlabeled EEG segments that are similar (close) or dissimilar (far) in time. It projects them in an embedding space accordingly, then reuses it to solve the real task. Our PT is based on Relative Positioning (RP) [3]. For T trials, it produces 2T pairs of similar EEG windows if they belong to the same segment, and 4T(2T-1) pairs of dissimilar ones if they come from different segments. Segments are related to resting or MI periods. The feature extractor is EEGNet [4] without its classification layer, and both pretext and real task classifiers are logistic regressions. Fig. 1 presents the accuracy of the CSSL models among different percentages of the training set, as the number of features extracted, i.e., the size *d* of the embedding space, varies. The process was cross-validated with 6-folds, and averaged across 10 repetitions (except for 100% of training data). CSSL is compared to LDA+CSP with 4 filters, which is better than 6.

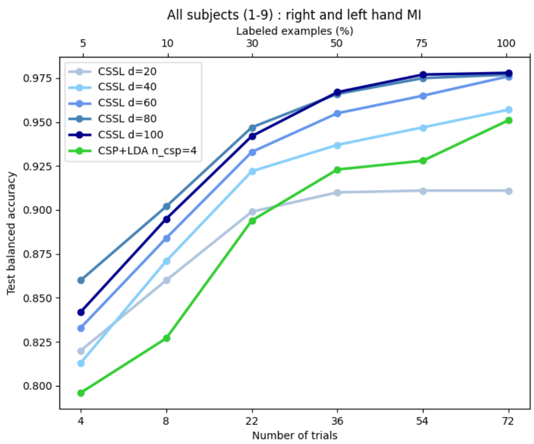

Figure 1. *Test accuracy, averaged across all subjects, for the detections of MI vs rest (BCI IV Competition dataset 2a), obtained by SSL models, as a function of the percentage of labeled training data. The embedding size is noted as* d.

Discussion and Significance: As *d* increases, the accuracy of CSSL models improves, from an accuracy above 80% when trained with only 4 trials, to nearly 98% with more than 54 trials. In particular, the accuracy for d=80 is better than for d=100 with smaller datasets, meaning that the performance saturates as the amount of features extracted increases. A Student test ($p < 0.05$) with a Šidák correction for 6 methods considers the different models almost two by two statistically equal due to the small sample size. Nevertheless, CSSL shows higher accuracies and confirms its capability to extract useful features from unlabeled data.

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