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A CSP-based retraining framework for motor imagery based brain-computer interfaces

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Motor imagery (MI) is a classic paradigm of electroencephalogram (EEG)-based brain-computer interfaces (BCIs). It entails individuals mentally imagining the movement of a body part without physically performing it. EEG signals from MI are induced by imagination of movement and do not rely on external stimuli. With minimal training, individuals can achieve autonomous control, making MI-based BCI systems highly convenient. During MI, specific regions of the cerebral cortex exhibit changes in sensory-motor rhythms (SMR), which is mainly manifested through event-related desynchronization (ERD) and event-related synchronization (ERS), which are noticeable power decrease and increase at specific frequency bands, respectively. Generally, ERD occurs on the contralateral side of the brain, whereas ERS occurs on the ipsilateral side. Therefore, detecting SMR in specific areas of the cerebral cortex from EEG can be used to decode the subject's motor intentions, and then control external devices to execute the corresponding movements. Many approaches have been proposed to distinguish the ERD/ERS patterns, which can be broadly categorized into traditional approaches and deep learning approaches.

Traditional approaches perform signal processing, feature extraction and classification separately. Many signal processing and feature extraction algorithms have been proposed, e.g., common spatial pattern (CSP), independent component analysis, autoregressive components, Riemannian geometry, tangent space features, recurrence quantification analysis, and so on [1]. Due to the SMR characteristic of MI-EEG, CSP is widely used to improve the spatial resolution, which transforms the raw EEG data into output data with optimal variance for subsequent feature extraction and classification. It was originally proposed for binary classification, but extensions to multi-class tasks and many other variants have also been proposed. In the classification phase, various traditional classifiers can be used on the extracted features, such as logistic regression (LR), support vector machine (SVM), linear discriminant analysis (LDA), and so on [1]. Traditional signal processing, feature extraction, and machine learning approaches may perform more robustly with small data; however, their performance may still need improvements. For example, the goal of CSP is to maximize the variance of the filtered EEG signals for different classes, which is related to but not completely consistent with the classification performance.

Deep learning approaches integrate signal processing, feature extraction, and classification into a single neural network, allowing end-to-end training with raw EEG data. For example, Schirrmeister et al. [2] proposed ShallowCNN and DeepCNN which include convolution kernels in temporal and spatial dimensions for raw EEG classification. Lawhern et al. [3] introduced EEGNet, a compact network that uses a depthwise convolution and a separable convolution for reducing the parameter count. Zhang et al. [4] proposed a hybrid deep neural network composed of convolution neural network (CNN) and long short-term memory (LSTM). Miao et al. [5] designed LMDA-Net, which includes a channel attention module and a depth attention module to extract features from multiple dimensions. However, these deep learning models have much more parameters than traditional models, and require more training data to avoid overfitting. Unfortunately, collecting EEG training data is time-consuming and user-unfriendly; publicly available MI datasets usually only contain a limited number of samples, resulting in degraded performance of the trained model.

This study proposes a retraining framework to combine prior knowledge from CSP and additional information from the raw EEG data for optimizing CSP and its variants based on traditional models. Specifically, the retraining framework consists of two stages: (1) traditional model training, where the CSP filters and a traditional classifier are designed, and (2) retraining, where an end-to-end neural network is initialized with the parameters of the traditional model and further optimized using gradient descent. Thus, the retraining framework complements prior knowledge from CSP with knowledge from the training data. The algorithm details on CSP and its variants will be given in Appendix A. Here we only introduce the overall CSP-based retraining framework.

Retraining framework. The objective of CSP is to maximize the variance difference of EEG signals between different classes, which is not completely consistent with the final classification objective. Our proposed retraining framework aims to exploit the prior knowledge from CSP and additional task-specific knowledge from the training data. It consists

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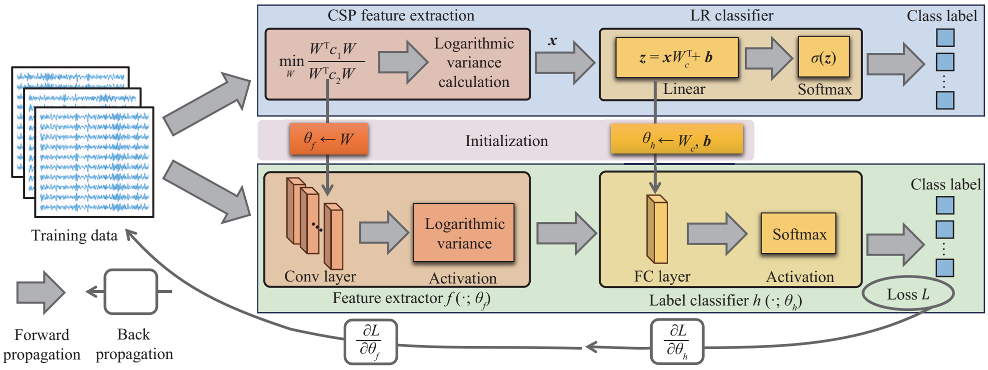

Figure 1 (Color online) CSP retraining framework, which consists of two stages. In the first stage (top blue block), a CSP-based traditional model is trained on the training data. In the second stage (bottom green block), a neural network is initialized with the same computational process and parameters as the traditional model, and then retrained using gradient descent.

of two training stages, as shown in Figure 1.

Stage 1. Traditional model training. A traditional classification pipeline with the CSP algorithm is applied to the training data. This includes CSP spatial filtering, feature extraction, and classifier optimization. Taking the classic CSP algorithm and LR classifier as an example, there are three steps: (1) Optimize the CSP filter matrix W using the objective of (A1) and each EEG trial is projected into a discriminative space by (A3) in Appendix A; (2) calculate a logarithmic variance feature vector $\boldsymbol{x}$ from each spatially filtered EEG trial by (A4) in Appendix A; and, (3) design an LR classifier with weights W_c and bias $\boldsymbol{b}$ to classify $\boldsymbol{x}$, where the softmax function $\sigma(\cdot)$ is used for multi-nominal LR model.

Stage 2. Retraining. A feed-forward neural network consisting of two blocks, each corresponding to a specific step in the traditional classification pipeline, is constructed.

The first block, defined as feature extractor f, consists of a convolutional layer with c' convolutional kernels of size $(c, 1)$ followed by a logarithmic variance activation, where c is the number of EEG channels and c' is consistent with the number of CSP filters. This block simulates the CSP filter and feature calculation process, mapping the raw EEG signal X into a feature vector $\boldsymbol{x}$, i.e.,

$$\boldsymbol{x} = f(X;\theta_f) = \log\left(\mathrm{var}\left(\mathrm{Conv}(X;\theta_f)\right)\right), \tag{1}$$

where θ_f is the parameter of the convolutional kernels, which has the same dimensionality as the CSP filter matrix W.

The second block, defined as classifier h, maps the feature vector $\boldsymbol{x}$ into a label y, which consists of a fully-connected layer with parameters θ_h followed by softmax activation for classification, i.e.,

$$p(y=i|\boldsymbol{x}) = h(\boldsymbol{x};\theta_h) = \sigma(\boldsymbol{x}\theta_{h_w}^{\mathrm{T}} + \theta_{h_b}). \tag{2}$$

The parameter θ_f in f is initialized with the CSP filter matrix W. θ_{h_w} and θ_{h_b} in h are initialized with the LR classifier weights W_c and bias $\boldsymbol{b}$, respectively, to introduce prior knowledge from the traditional model. During retraining, the model parameters are further optimized to minimize the following empirical loss on the training samples using gradient descent:

$$L = -\frac{1}{N}\sum_{n}^{N}\sum_{i}^{C}\mathbb{I}(y_n=i)\log\left(h(f(X_n;\theta_f);\theta_h)\right), \tag{3}$$

where $\mathbb{I}(\cdot)$ is the indicator function, N is the number of training samples, and C is the number of class labels.

We verified the effectiveness of the retraining framework with the standard CSP algorithm and its two variants across a wide range of testing scenarios with more advantages in small-sample settings. Detailed experimental results and analysis can be found in Appendix B.

Conclusion. CSP is one of the most widely used signal processing approaches in EEG-based MI classification; however, the CSP optimization objective is not completely consistent with the final classification objective, and hence it does not necessarily lead to the best classification performance. This study has proposed a retraining framework, which retrains a neural network with the same forward computational process and initial parameters as the CSP-based traditional model, and further optimizes it on the labeled training data using gradient descent. Experiments on four MI datasets demonstrated that retraining improved traditional models' classification performance and outperformed several popular deep neural network models, especially when the amount of labeled training data was very small. Our work demonstrates the advantage of integrating knowledge from traditional models and from the training data in EEG-based BCIs.

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Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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