

• Supplementary File •

A CSP-Based Retraining Framework for Motor Imagery Based Brain-Computer Interfaces

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Appendix A Related Work

Appendix A.1 CSP

The CSP algorithm is popular for processing multi-channel EEG signals [1,2]. Initially proposed by Koles *et al.* [3], it was designed for extracting discriminative features from EEG signals of two human populations and was later introduced into MI classification by Ramoser *et al.* [1] and Müller-Gerking [4]. In binary classification, CSP aims to learn a set of spatial filters that maximize the variance of EEG signals from one class while minimizing the variance from the other class [2].

Let $X_i \in \mathbb{R}^{c \times t}$ be an EEG trial of MI task i , where $i \in \{1, 2\}$ is the class index, c the number of channels, and t the number of time domain samples per channel. CSP optimizes a spatial filtering matrix $W \in \mathbb{R}^{c \times c'}$ ($c' < c$) that projects the original EEG trials into a lower-dimensional space with higher discriminability. W is obtained by maximizing (or minimizing)

$$J(W) = \frac{W^\top \bar{X}_1 \bar{X}_1^\top W}{W^\top \bar{X}_2 \bar{X}_2^\top W} = \frac{W^\top \bar{C}_1 W}{W^\top \bar{C}_2 W}, \quad (\text{A1})$$

where $\bar{X}_i \in \mathbb{R}^{c \times t}$ is the average EEG trial from class i , and $\bar{C}_i \in \mathbb{R}^{c \times c}$ the mean spatial covariance matrix of all EEG trials in class i .

Since $J(W) = J(kW)$ for any arbitrary real constant k , maximizing $J(W)$ is equivalent to maximizing $W^\top \bar{C}_1 W$, subject to the constraint $W^\top \bar{C}_2 W = I_{c'}$. This optimization problem can be solved using the Lagrange multiplier method [5], whose Lagrange function is

$$F(W, \lambda) = W^\top \bar{C}_1 W - \lambda(W^\top \bar{C}_2 W - I_{c'}). \quad (\text{A2})$$

Setting the derivative of $F(W, \lambda)$ with respect to W to 0, we have

$$\begin{aligned} \frac{\partial F(W, \lambda)}{\partial W} &= 2W^\top \bar{C}_1 - 2\lambda W^\top \bar{C}_2 = 0 \\ &\Leftrightarrow \bar{C}_1 W = \lambda \bar{C}_2 W \\ &\Leftrightarrow \bar{C}_2^{-1} \bar{C}_1 W = \lambda W, \end{aligned}$$

which becomes a standard eigenvalue decomposition problem.

The spatial filtering matrix W consists of eigenvectors corresponding to the $\frac{c'}{2}$ largest and the $\frac{c'}{2}$ smallest eigenvalues of $\bar{C}_2^{-1} \bar{C}_1$.

Then, CSP projects an EEG trial $X \in \mathbb{R}^{c \times t}$ to $X' \in \mathbb{R}^{c' \times t}$ by

$$X' = W^\top X. \quad (\text{A3})$$

To obtain the feature vector for classification, the logarithmic variance of the spatially filtered EEG trial is then calculated as:

$$\mathbf{x} = \log(\text{var}(X')). \quad (\text{A4})$$

Finally, the feature vector \mathbf{x} can be used as the input to a classifier, e.g., LR or SVM.

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Appendix A.2 TRCSP

Despite the effectiveness of the classic CSP algorithm, it is sensitive to noise and susceptible to overfitting [6]. RCSP algorithms have been proposed [7–9] to address these limitations, using different regularization strategies.

One strategy [8, 9] is to regularize the covariance matrix estimation, which is easily influenced by noise and/or insufficient data. It borrows EEG data from other subjects, which may exhibit large individual differences.

Another strategy [5] adds a regularization term, which imposes priors on the spatial filters [7, 10], to the CSP objective function (A1):

$$J_{P_1}(W) = \frac{W^\top \bar{C}_1 W}{W^\top \bar{C}_2 W + \alpha P(W)}, \quad (\text{A5})$$

where $P(W)$ is a penalty function that evaluates how well the spatial filter matrix W satisfies a given prior, and α a regularization parameter.

A specific implementation, Tikhonov RCSP (TRCSP), uses the classic form of Tikhonov regularization, i.e., $P(W) = \|W\|^2 = W^\top W = W^\top I_{c'} W$, where $I_{c'}$ is a $c' \times c'$ identity matrix. Then, (A5) becomes

$$\begin{aligned} J_{P_1}(W) &= \frac{W^\top \bar{C}_1 W}{W^\top \bar{C}_2 W + \alpha W^\top I_{c'} W} \\ &= \frac{W^\top \bar{C}_1 W}{W^\top (\bar{C}_2 + \alpha I_{c'}) W}. \end{aligned}$$

The corresponding Lagrange function is

$$F_{P_1}(W, \lambda) = W^\top \bar{C}_1 W - \lambda (W^\top (\bar{C}_2 + \alpha I_{c'}) W - I_{c'}). \quad (\text{A6})$$

Similar to the classic CSP, we obtain the following eigenvalue problem:

$$(\bar{C}_2 + \alpha I_{c'})^{-1} \bar{C}_1 W = \lambda W. \quad (\text{A7})$$

The filters maximizing $J_{P_1}(W)$ are the eigenvectors corresponding to the $\frac{c'}{2}$ largest eigenvalues of the matrix $(\bar{C}_2 + \alpha I_{c'})^{-1} \bar{C}_1$. Similarly, to obtain the filters that maximize C_2 and simultaneously minimize C_1 , we maximize the following objective function:

$$J_{P_2}(W) = \frac{W^\top \bar{C}_2 W}{W^\top \bar{C}_1 W + \alpha W^\top I_{c'} W}. \quad (\text{A8})$$

The filters are the eigenvectors corresponding to the $\frac{c'}{2}$ largest eigenvalues of the matrix $(\bar{C}_1 + \alpha I_{c'})^{-1} \bar{C}_2$.

After obtaining the spatial filters, the TRCSP feature vector is calculated similar to that in the classic CSP algorithm.

Appendix A.3 FBCSP

The effectiveness of CSP features depends on the operational frequency band [11]. FBCSP [12] extracts CSP features from multiple different frequency bands, which may be more robust than using a single frequency band.

FBCSP first bandpass filters the raw EEG signals into multiple frequency bands. Then, it computes spatial filters using the classic CSP algorithm described in Appendix A.1 and extracts CSP features from each individual frequency band. As the concatenated features have much higher dimensionality than those from the classic CSP algorithm, feature selection may also be performed.

Appendix B Experiments and Results

Appendix B.1 Datasets

Four public MI datasets from BNCI-Horizon¹⁾, summarized in Table B1, were used to validate the retraining framework:

1. MI9S: This is the 001-2015 dataset, with EEG signals recorded at 512Hz. The last three subjects were discarded due to poor performance [13, 14].
2. MI14S: This is the 002-2014 dataset, with EEG signals sampled at 512Hz.
3. MI2C: This is the 001-2014 dataset, with EEG signals sampled at 250Hz. The left-hand and right-hand trials were used in our experiments.
4. MI4C: This is the 001-2014 dataset with all classes.

All four datasets were downloaded and pre-processed using MOABB [15], and an 8-32Hz bandpass filter was applied.

1) <https://www.bnci-horizon-2020.eu/database/data-sets>.

Table B1 Summary of the four MI datasets.

Dataset	# Subjects	# Channels	# Trials per subject	# Classes
MI9S	9	13	200	2
MI14S	14	15	100	2
MI2C	9	22	144	2
MI4C	9	22	288	4

Appendix B.2 Implementation Details

We evaluated the performance of the retraining framework in both within-subject and cross-subject classification scenarios:

1. Within-subject evaluation: For each individual subject, 80% trials were used for training, and the remaining 20% for testing.
2. Cross-subject evaluation: Leave-one-subject-out cross-validation was performed, i.e., one subject was used as the test set and all remaining ones were combined as the training set.

We applied the retraining framework to the standard CSP algorithm and its two variants, TRCSP and FBCSP. CSP and TRCSP each had 8 spatial filters. FBCSP used two frequency bands for bandpass filtering and no feature selection, so the total number of spatial filters was $2 \times 8 = 16$. TRCSP used $\alpha = 0.01$ in regularization. LR was used as the default traditional classifier. In the retraining network, parameters θ_f of the convolutional layer of f were initialized to the spatial filter matrix W , parameters θ_{h_w} and θ_{h_b} in the fully-connected layer of h were initialized to the LR parameters W_c and \mathbf{b} .

We calculated the mean accuracies across all subjects as the performance metric. All experiments were repeated 5 times, and the average results are reported.

Appendix B.3 Performance Metrics

We used the following two metrics to evaluate the classification performance:

- Classification accuracy (acc), which is the ratio of the number of correct predictions to the total number of test samples. It is calculated by

$$\text{acc} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}. \quad (\text{B1})$$

- Kappa value, or Cohen’s kappa (kappa), which evaluates the agreement between predicted and actual classifications beyond chance, with values from -1 to 1. The formula is

$$\text{kappa} = \frac{P_o - P_e}{1 - P_e}, \quad (\text{B2})$$

where P_o is the observed accuracy and P_e the expected accuracy by chance.

Appendix B.4 Within-Subject Classification Results

To study EEG-based MI classification in a small-sample setting, we performed experiments with different data ratios (the number of trials used to train the model divided by the total number of training trials). Tables B2-B5 show the within-subject classification accuracy on each subject and average accuracy (kappa) values across four datasets, respectively. We also performed paired t -tests on the results, calculated p -values between the standard traditional models and the retraining framework, and adjusted them using Benjamini Hochberg False Discovery Rate correction.

As the data ratio increased, all approaches had better performance, which is intuitive; however, retraining consistently achieved better or comparable performance with the CSP, TRCSP and FBCSP baselines. Moreover, retraining exhibited more noticeable improvements in small-sample scenarios, e.g., 10% data ratio, demonstrating that transferring knowledge from traditional approaches can indeed help reduce the overfitting of deep neural networks.

Appendix B.5 Cross-Subject Classification Results

Figure B1 shows the cross-subject classification results when the data ratio increased from 1% to 100%. Considering the individual differences in cross-subject scenario, we incorporated several neural network based domain adaptation approaches into the FBCSP based retraining framework, including DAN [16], CDAN [17] and MCC [18]. All of them using the same backbone as in retraining framework, with their respective domain adaptation loss function calculated on source subject data and unlabeled target subject data.

We can observe that:

1. Retraining consistently outperformed CSP, TRCSP and FBCSP.
2. Incorporating domain adaptation into the retraining framework further enhanced the performance. Particularly, Retraining-MCC achieved overall the best performance across different datasets and data ratios.
3. Similar to within-subject classification, retraining performed better in small-sample scenarios. For example, with a data ratio of only 1%, CSP, TRCSP and FBCSP had near-random performance, whereas retraining noticeably improved it.

Table B2 Within-subject classification accuracies (%) on MI9S. Higher average accuracy or kappa values from retraining are marked in bold. Asterisks indicate statistically significant differences between comparison baseline and retraining under adjusted paired *t*-test, where * means $p < 0.05$, ** means $p < 0.01$, *** means $p < 0.001$.

Data ratio	Approach		S1	S2	S3	S4	S5	S6	S7	S8	S9	Average acc±std(kappa)
10%	CSP	Standard	64.28	51.50	55.99	54.62	49.17	54.41	55.29	50.28	49.48	53.89***±1.11(0.08±0.02)
		Retraining	70.20	56.04	74.39	59.85	54.04	52.89	55.88	53.91	50.72	58.66 ±1.14(0.17 ±0.02)
	TRCSP	Standard	64.58	52.00	54.84	56.32	48.07	53.39	54.76	50.80	52.94	54.19**±1.89(0.08±0.04)
		Retraining	70.89	54.01	68.86	62.13	55.04	55.47	56.18	52.90	53.74	58.80 ±2.64(0.17 ±0.05)
	FBCSP	Standard	66.14	53.51	59.15	58.68	49.57	50.56	53.02	50.88	52.02	54.84**±2.05(0.09±0.04)
		Retraining	69.26	66.77	68.78	59.37	52.08	50.47	64.30	54.77	52.43	59.80 ±1.67(0.19 ±0.03)
	Average	Standard	65.00	52.34	56.66	56.54	48.94	52.79	54.36	50.65	51.48	54.31***±1.77(0.08±0.03)
		Retraining	70.12	58.94	70.68	60.45	53.72	52.94	58.79	53.86	52.30	59.09 ±2.00(0.18 ±0.04)
20%	CSP	Standard	70.83	62.32	74.74	56.05	54.40	53.63	55.14	56.29	52.66	59.56*±1.97(0.19±0.04)
		Retraining	73.51	70.77	79.88	62.41	51.78	56.42	58.24	62.21	52.85	63.12 ±3.07(0.26 ±0.06)
	TRCSP	Standard	69.47	59.33	74.30	59.20	56.18	55.29	53.66	54.07	53.97	59.50*±2.96(0.19±0.06)
		Retraining	71.81	74.58	80.02	63.91	51.98	54.66	63.58	59.64	53.14	63.70 ±3.29(0.27 ±0.06)
	FBCSP	Standard	71.95	69.01	81.29	62.48	59.29	50.52	57.24	56.88	54.22	62.54*±3.59(0.25±0.07)
		Retraining	76.82	75.72	80.31	65.04	61.04	55.33	65.80	58.59	49.89	65.39 ±2.37(0.30 ±0.05)
	Average	Standard	70.75	63.55	76.78	59.24	56.62	53.15	55.35	55.75	53.62	60.53***±3.25(0.21±0.06)
		Retraining	74.05	73.69	80.07	63.79	54.93	55.47	62.54	60.15	51.96	64.07 ±2.00(0.28 ±0.06)
30%	CSP	Standard	78.42	61.10	79.55	59.21	52.79	54.01	56.18	52.40	47.76	60.16**±1.20(0.20±0.03)
		Retraining	73.65	65.83	82.51	67.84	49.50	57.74	68.10	63.28	52.31	64.53 ±2.37(0.28 ±0.04)
	TRCSP	Standard	77.95	61.90	84.05	60.15	53.63	55.00	55.65	52.73	49.21	61.14*±2.17(0.22±0.04)
		Retraining	64.49	70.39	85.52	67.93	50.69	56.98	72.21	56.50	55.26	64.44 ±2.50(0.28 ±0.05)
	FBCSP	Standard	79.49	72.33	79.61	66.70	56.49	53.80	60.85	56.07	51.06	64.05**±3.90(0.27±0.08)
		Retraining	81.16	78.76	80.96	66.09	61.63	56.08	67.07	65.01	46.76	67.06 ±3.27(0.34 ±0.06)
	Average	Standard	78.62	65.11	81.07	62.02	54.30	54.27	57.56	53.73	49.34	61.78***±3.14(0.23±0.06)
		Retraining	73.10	71.66	83.00	67.29	53.94	56.93	69.13	61.60	51.44	65.34 ±3.00(0.30 ±0.06)
40%	CSP	Standard	79.92	63.32	81.73	69.50	55.98	55.91	59.18	56.24	48.71	63.39±2.33(0.26±0.05)
		Retraining	66.41	70.55	85.83	67.72	56.35	60.72	67.96	65.06	48.91	65.50 ±3.90(0.31 ±0.08)
	TRCSP	Standard	80.39	64.66	80.99	67.42	58.05	56.44	61.03	50.02	47.74	62.97±2.09(0.25±0.04)
		Retraining	66.06	72.31	87.84	67.25	59.79	64.13	69.44	56.93	48.71	65.83 ±3.07(0.31 ±0.06)
	FBCSP	Standard	83.43	73.65	80.88	72.47	58.83	57.19	63.18	54.80	47.54	65.78*±3.58(0.31±0.07)
		Retraining	73.82	82.68	85.19	73.55	64.12	55.77	67.81	60.10	53.52	68.51 ±3.33(0.36 ±0.07)
	Average	Standard	81.25	67.21	81.20	69.80	57.62	56.51	61.13	53.69	48.00	64.05*±3.01(0.28±0.06)
		Retraining	68.76	75.18	86.29	69.51	60.09	60.21	68.40	60.70	50.38	66.61 ±3.00(0.33 ±0.07)
50%	CSP	Standard	78.86	67.47	84.50	67.22	57.51	57.18	62.80	54.63	50.87	64.56**±3.16(0.28±0.06)
		Retraining	74.46	76.25	87.63	71.15	58.99	62.60	68.75	67.91	49.39	68.57 ±2.96(0.37 ±0.06)
	TRCSP	Standard	80.61	69.02	85.70	64.89	60.07	58.78	63.80	53.22	50.98	65.23±3.29(0.30±0.06)
		Retraining	68.54	74.45	90.48	71.41	57.81	62.96	70.37	60.02	51.02	67.45 ±4.40(0.34 ±0.09)
	FBCSP	Standard	85.77	76.41	80.19	72.51	57.71	59.73	65.17	53.66	51.76	66.99*±1.68(0.33±0.04)
		Retraining	80.03	80.65	84.57	70.72	58.54	58.66	71.36	64.21	50.46	68.80 ±1.80(0.37 ±0.04)
	Average	Standard	81.75	70.97	83.46	68.21	58.43	58.56	63.92	53.84	51.20	65.59**±2.99(0.30±0.06)
		Retraining	74.34	77.12	87.56	71.09	58.45	61.41	70.16	64.05	50.29	68.27 ±2.00(0.36 ±0.06)
100%	CSP	Standard	84.15	75.85	84.17	71.31	63.11	61.64	64.16	59.31	46.81	67.84±2.26(0.35±0.04)
		Retraining	77.05	76.70	88.14	74.87	66.50	65.89	66.59	61.55	50.02	69.70 ±3.68(0.39 ±0.07)
	TRCSP	Standard	84.89	76.81	83.60	69.38	63.72	64.27	68.52	60.47	48.66	68.92±2.46(0.37±0.05)
		Retraining	69.26	68.83	87.37	73.31	68.29	68.02	69.16	58.40	52.74	68.37±4.32(0.37±0.09)
	FBCSP	Standard	86.55	78.45	87.03	71.85	62.44	66.10	67.28	58.07	46.59	69.37**±1.81(0.38±0.03)
		Retraining	87.36	81.66	87.77	77.85	73.00	62.97	73.00	63.29	51.46	73.15 ±3.43(0.46 ±0.07)
	Average	Standard	85.20	77.04	84.93	70.85	63.09	64.00	66.65	59.28	47.35	68.71*±2.29(0.36±0.04)
		Retraining	77.89	75.73	87.76	75.34	69.26	65.63	69.58	61.08	51.41	70.41 ±3.00(0.40 ±0.08)

Table B4 Within-subject classification accuracies (%) on MI2C. Higher average accuracy or kappa values from retraining are marked in bold. Asterisks indicate statistically significant differences between comparison baseline and retraining under adjusted paired *t*-test, where * means $p < 0.05$, ** means $p < 0.01$, *** means $p < 0.001$.

Data ratio	Approach		S1	S2	S3	S4	S5	S6	S7	S8	S9	Average acc±std(kappa)
10%	CSP	Standard	52.23	51.33	65.14	52.51	49.43	50.60	52.70	55.67	52.77	53.60***±2.00(0.07±0.04)
		Retraining	57.96	51.84	78.96	55.43	43.93	56.84	63.66	82.51	59.89	61.22 ±1.67(0.22 ±0.03)
	TRCSP	Standard	54.45	50.64	64.78	53.55	49.43	48.49	54.44	57.20	51.33	53.81***±2.15(0.08±0.05)
		Retraining	66.36	50.74	84.62	50.72	43.77	51.75	57.94	82.86	61.90	61.18 ±2.41(0.22 ±0.05)
	FBCSP	Standard	51.85	54.21	66.85	51.67	50.59	51.72	49.97	58.10	56.37	54.59***±2.49(0.09±0.05)
		Retraining	60.08	60.25	74.68	53.76	50.51	56.48	48.76	75.39	66.01	60.66 ±2.67(0.21 ±0.05)
	Average	Standard	52.84	52.06	65.59	52.58	49.82	50.27	52.37	56.99	53.49	54.00***±2.27(0.08±0.05)
		Retraining	61.47	54.28	79.42	53.30	46.07	55.02	56.79	80.25	62.60	61.02 ±2.67(0.22 ±0.05)
20%	CSP	Standard	67.11	48.38	85.29	58.10	50.89	54.12	56.75	85.28	63.55	63.28*±1.88(0.27±0.04)
		Retraining	62.93	53.03	88.89	64.52	49.43	58.76	56.74	86.54	77.15	66.44 ±1.85(0.32 ±0.04)
	TRCSP	Standard	65.76	52.14	81.72	56.95	51.74	49.92	57.56	86.84	62.63	62.81*±2.05(0.26±0.04)
		Retraining	62.39	57.82	91.43	62.36	47.18	64.10	57.53	87.45	76.42	67.41 ±3.34(0.34 ±0.06)
	FBCSP	Standard	66.00	50.97	80.13	57.68	51.81	57.08	55.99	83.18	63.76	62.96±1.54(0.26±0.03)
		Retraining	64.12	54.74	90.54	52.30	46.84	58.00	53.27	81.07	76.42	64.14 ±1.50(0.28 ±0.03)
	Average	Standard	66.29	50.50	82.38	57.58	51.48	53.71	56.77	85.10	63.31	63.02**±1.85(0.26±0.04)
		Retraining	63.15	55.20	90.29	59.73	47.82	60.29	55.85	85.02	76.66	66.00 ±1.50(0.32 ±0.05)
30%	CSP	Standard	68.15	55.22	84.04	61.07	52.03	58.28	71.43	89.32	65.84	67.27±3.97(0.34±0.07)
		Retraining	67.05	51.71	91.10	63.38	48.01	62.74	64.53	86.39	76.05	67.89 ±1.21(0.35 ±0.02)
	TRCSP	Standard	67.29	59.17	87.75	58.37	53.37	55.33	66.42	91.63	68.51	67.54±1.76(0.35±0.03)
		Retraining	65.12	53.75	91.87	58.74	50.66	59.43	65.92	89.61	72.76	67.54±0.49(0.35±0.01)
	FBCSP	Standard	71.76	56.95	88.00	62.56	54.81	59.09	60.19	82.60	71.00	67.44±1.84(0.34±0.04)
		Retraining	73.00	55.13	94.32	61.67	53.59	58.28	58.82	79.50	77.81	68.01 ±2.95(0.36 ±0.06)
	Average	Standard	69.07	57.11	86.60	60.67	53.40	57.57	66.01	87.85	68.45	67.42±2.73(0.34±0.05)
		Retraining	68.39	53.53	92.43	61.26	50.75	60.15	63.09	85.17	75.54	67.81 ±2.95(0.35 ±0.04)
40%	CSP	Standard	72.10	53.43	94.04	67.56	54.62	61.81	66.40	92.03	70.31	70.26±1.61(0.40±0.03)
		Retraining	74.13	56.90	91.61	67.66	52.01	64.20	70.67	90.10	75.53	71.42 ±1.88(0.43 ±0.04)
	TRCSP	Standard	70.15	53.81	92.30	59.01	55.25	61.57	66.87	93.92	79.14	70.22±2.55(0.40±0.05)
		Retraining	72.96	53.60	95.02	66.06	54.82	61.86	71.85	93.03	76.10	71.70 ±1.15(0.43 ±0.02)
	FBCSP	Standard	77.23	58.11	93.59	66.28	52.68	61.14	63.94	89.58	76.28	70.98±1.64(0.42±0.03)
		Retraining	76.12	56.37	93.22	65.13	51.93	67.36	61.23	83.64	77.19	70.24±1.82(0.40±0.04)
	Average	Standard	73.16	55.12	93.31	64.28	54.18	61.51	65.74	91.84	75.24	70.49±2.01(0.41±0.04)
		Retraining	74.40	55.62	93.28	66.28	52.92	64.47	67.92	88.92	76.27	71.12 ±1.82(0.42 ±0.04)
50%	CSP	Standard	76.45	58.11	94.95	67.91	51.93	60.68	66.74	93.84	75.81	71.82±1.15(0.43±0.02)
		Retraining	77.19	53.98	92.65	71.43	53.03	65.32	66.79	92.08	75.91	72.04 ±1.47(0.44 ±0.03)
	TRCSP	Standard	75.03	54.80	92.90	64.73	52.49	64.44	67.78	94.58	78.00	71.64±0.51(0.43±0.01)
		Retraining	73.69	57.82	96.24	68.68	51.76	60.43	67.35	95.65	76.40	72.00 ±0.95(0.44 ±0.02)
	FBCSP	Standard	79.71	53.66	95.57	63.20	50.55	63.14	63.89	88.86	76.76	70.59*±2.64(0.41±0.05)
		Retraining	81.43	56.27	94.39	67.02	56.15	62.44	69.52	89.49	80.92	73.07 ±1.92(0.46 ±0.04)
	Average	Standard	77.06	55.52	94.47	65.28	51.66	62.75	66.14	92.43	76.86	71.35±1.77(0.42±0.03)
		Retraining	77.44	56.02	94.43	69.04	53.65	62.73	67.89	92.41	77.74	72.37 ±1.92(0.44 ±0.03)
100%	CSP	Standard	78.89	59.15	96.69	74.81	48.87	64.34	74.93	95.30	77.20	74.46*±1.30(0.49±0.02)
		Retraining	82.35	59.99	92.68	70.43	50.69	64.95	68.14	92.64	74.31	72.91±2.81(0.46±0.06)
	TRCSP	Standard	82.11	59.86	95.58	76.73	50.93	64.34	75.01	94.13	78.77	75.27±2.40(0.51±0.05)
		Retraining	81.87	55.71	95.10	73.46	47.33	65.97	72.16	98.56	78.92	74.34±1.36(0.49±0.03)
	FBCSP	Standard	85.58	61.83	97.49	73.15	61.31	68.88	72.49	91.94	77.81	76.72±1.63(0.53±0.03)
		Retraining	84.70	62.65	99.41	70.70	59.81	69.35	77.58	93.01	81.25	77.61 ±1.74(0.55 ±0.03)
	Average	Standard	82.19	60.28	96.59	74.90	53.70	65.85	74.14	93.79	77.93	75.48*±1.90(0.51±0.04)
		Retraining	82.97	59.45	95.73	71.53	52.61	66.76	72.63	94.74	78.16	74.95±1.74(0.50±0.06)

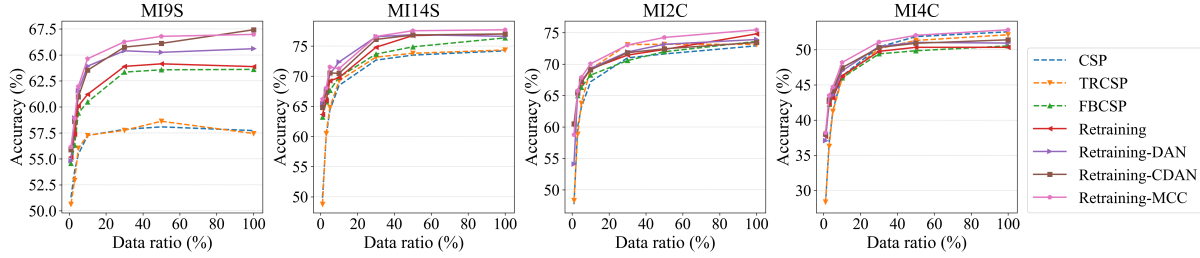


Figure B1 Cross-subject classification accuracies on the four datasets.

Appendix B.6 Comparison with Traditional Classifiers

The above experiments used LR as the classifier. This subsection compares FBCSP-LR based retraining with additional traditional classifiers. Note that the data split kept the same across different models to ensure the fairness.

Table B6 shows the results on the four datasets, where FBCSP filtering was used for signal processing, and MCC in cross-subject classification. Again, FBCSP-LR based retraining almost always achieved the best performance. Note that at the same data ratio, there is more training data for cross-subject experiments. Additionally, MCC can further reduce subject differences, potentially leading to better results compared to within-subject experiments.

Appendix B.7 Comparison with Deep Neural Network Models

In addition to traditional models, deep neural network (DNN) models are commonly used for MI classification. This subsection compares FBCSP-LR based retraining with several commonly used convolutional neural networks (CNNs) in EEG-based MI classification, including EEGNet [19], DeepCNN [20] and ShallowCNN [20], a CNN+LSTM model [21], and an attention-based network, LMDA-Net [22]. Note that the data split and training strategies kept the same, making the comparison fair for all models.

Table B7 shows the results on the four datasets, where MCC was used in cross-subject classification of retraining. Retraining outperformed the DNN models in both within-subject and cross-subject scenarios in most cases.

Appendix B.8 Ablation Study

We conducted an ablation study to validate if retraining both f and h is necessary. Two baselines were compared:

1. Retraining-Rand, which randomly initializes θ_f in the convolutional layer of the feature extractor f and θ_h in the fully-connected layer of the classifier h .
2. Retraining-Fix f , which initializes θ_f with the spatial filter matrix W and randomly initializes parameters θ_h in the classifier, and then fixes θ_f and only updates θ_h .

Table B8 shows the results with a 30%/3% data ratio in within/cross-subject scenarios, to maintain consistency in the number of training samples. The accuracies of Retraining-Rand and Retraining-Fix f were comparable with those of CSP-LR, but lower than those of Retraining, suggesting the necessity of initializing both θ_f and θ_h from the traditional algorithms and then fine-tuning them in retraining.

Appendix B.9 Parameter Sensitivity Analysis

Table B9 shows the CSP-Retraining performance with different numbers of spatial filters in within-subject and cross-subject classification. The retraining performance was insensitive to the number of spatial filters and consistently better than CSP-LR.

Table B10 presents the FBCSP-Retraining performance with different number of frequency bands in within-subject and cross-subject classification. As the number of frequency bands increases, the number of trainable parameters of the model also increases, making it easier to overfit in small-sample scenarios.

Appendix B.10 Ensemble Learning

The retraining framework includes two models, i.e., the CSP-based traditional model and the retrained model. It is interesting to know if ensemble learning can be used to further improve the performance.

Three ensemble learning strategies, i.e., adaptive boosting [23], gradient boosting [24], and simple averaging, were used to aggregate the two models. Figure B2 shows the results on binary classification tasks. When the data ratio was small, adaptive boosting was generally beneficial; however, as the data ratio became large, averaging may be more advantageous. In summary, it is possible to use ensemble learning to further improve the classification performance in the retraining framework.

References

- 1 Ramoser H, Müller-Gerking J, Pfurtscheller G. Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE Trans Neural Syst Rehabil Eng*, 2000, 8: 441–446
- 2 Blankertz B, Tomioka R, Lemm S, et al. Optimizing spatial filters for robust EEG single-trial analysis. *IEEE Signal Process Mag*, 2008, 25: 41–56
- 3 Koles Z J, Lazar M S, Zhou S Z. Spatial patterns underlying population differences in the background EEG. *Brain Topogr*, 1990, 2: 275–284
- 4 Müller-Gerking J, Pfurtscheller G, Flyvbjerg H. Designing optimal spatial filters for single-trial EEG classification in a movement task. *Clin Neurophysiol*, 1999, 110: 787–798
- 5 Lotte F, Guan C T. Regularizing common spatial patterns to improve BCI designs: unified theory and new algorithms. *IEEE Trans Biomed Eng*, 2-10, 58: 355–362

Table B6 Classification accuracies (%) and kappa values of traditional classifiers and retraining with different data ratios. The highest accuracies or kappa values on each dataset are marked in bold.

Dataset	Scenario	Approach	Data ratio (%)					
			10	20	30	40	50	100
MI9S	Within-Subject	FBCSP-LR	54.84(0.10)	62.54(0.25)	64.05(0.28)	65.78(0.32)	66.99(0.34)	69.37(0.39)
		FBCSP-SVM	55.95(0.12)	59.51(0.19)	63.75(0.28)	64.27(0.29)	65.63(0.31)	69.66(0.39)
		FBCSP-LDA	55.67(0.11)	63.30(0.27)	65.36(0.31)	65.89(0.32)	67.78(0.36)	69.86(0.40)
		FBCSP-Retraining	59.80(0.20)	65.39(0.31)	67.06(0.34)	68.51(0.37)	68.80(0.38)	73.15(0.46)
	Cross-Subject	FBCSP-LR	61.42(0.23)	62.24(0.24)	62.44(0.25)	62.89(0.26)	63.57(0.27)	63.61(0.27)
		FBCSP-SVM	62.12(0.24)	62.27(0.25)	62.37(0.25)	62.39(0.25)	62.99(0.26)	63.73(0.27)
		FBCSP-LDA	61.00(0.22)	62.29(0.25)	62.41(0.25)	63.04(0.26)	64.29(0.29)	63.11(0.26)
		FBCSP-Retraining	64.63(0.29)	65.26(0.31)	66.27(0.33)	66.26(0.33)	66.79(0.34)	66.98(0.34)
MI14S	Within-Subject	FBCSP-LR	56.67(0.13)	62.11(0.24)	65.99(0.32)	69.64(0.39)	70.80(0.42)	75.39(0.51)
		FBCSP-SVM	57.57(0.15)	60.15(0.20)	65.81(0.32)	68.92(0.38)	72.80(0.46)	76.00(0.52)
		FBCSP-LDA	59.43(0.19)	58.12(0.16)	64.87(0.30)	66.74(0.33)	69.18(0.38)	75.63(0.51)
		FBCSP-Retraining	58.76(0.18)	64.60(0.29)	68.07(0.36)	69.59(0.39)	70.13(0.40)	73.77(0.48)
	Cross-Subject	FBCSP-LR	68.71(0.37)	71.20(0.42)	73.73(0.47)	74.44(0.49)	74.53(0.49)	76.36(0.53)
		FBCSP-SVM	69.20(0.38)	71.57(0.43)	73.69(0.47)	74.20(0.48)	74.79(0.50)	75.93(0.52)
		FBCSP-LDA	67.70(0.35)	70.91(0.42)	73.47(0.47)	74.49(0.49)	74.60(0.49)	75.43(0.51)
		FBCSP-Retraining	71.26(0.43)	74.99(0.50)	76.59(0.53)	77.43(0.55)	77.54(0.55)	77.70(0.55)
MI2C	Within-Subject	FBCSP-LR	54.59(0.09)	62.96(0.26)	67.44(0.35)	70.98(0.42)	70.59(0.41)	76.72(0.53)
		FBCSP-SVM	55.03(0.10)	59.28(0.19)	67.92(0.36)	70.77(0.42)	70.98(0.42)	76.82(0.54)
		FBCSP-LDA	57.33(0.15)	60.14(0.20)	66.44(0.33)	69.16(0.38)	71.07(0.42)	76.39(0.53)
		FBCSP-Retraining	60.66(0.21)	64.14(0.28)	68.01(0.36)	70.24(0.40)	73.07(0.46)	77.61(0.55)
	Cross-Subject	FBCSP-LR	64.57(0.29)	67.70(0.35)	70.15(0.40)	70.77(0.42)	71.31(0.43)	73.30(0.47)
		FBCSP-SVM	65.91(0.32)	67.73(0.35)	69.83(0.40)	70.68(0.41)	71.33(0.43)	73.36(0.47)
		FBCSP-LDA	64.72(0.29)	66.44(0.33)	68.77(0.38)	69.83(0.40)	70.09(0.40)	70.99(0.42)
		FBCSP-Retraining	70.05(0.40)	70.08(0.40)	73.04(0.46)	73.12(0.46)	74.24(0.48)	75.46(0.51)
MI4C	Within-Subject	FBCSP-LR	34.08(0.12)	44.36(0.26)	50.50(0.34)	56.49(0.42)	59.56(0.46)	66.81(0.56)
		FBCSP-SVM	39.47(0.19)	48.42(0.31)	53.76(0.38)	57.86(0.44)	59.55(0.46)	66.03(0.55)
		FBCSP-LDA	36.48(0.15)	49.86(0.33)	55.67(0.41)	57.66(0.44)	60.69(0.48)	67.63(0.57)
		FBCSP-Retraining	44.07(0.25)	49.28(0.32)	53.69(0.38)	56.85(0.42)	60.53(0.47)	66.46(0.55)
	Cross-Subject	FBCSP-LR	43.18(0.24)	47.07(0.29)	47.71(0.30)	48.90(0.32)	49.56(0.33)	50.54(0.34)
		FBCSP-SVM	43.64(0.25)	47.25(0.30)	47.37(0.30)	48.57(0.31)	48.88(0.32)	49.66(0.33)
		FBCSP-LDA	42.40(0.23)	46.22(0.28)	46.51(0.29)	47.84(0.30)	47.75(0.30)	48.30(0.31)
		FBCSP-Retraining	48.19(0.31)	51.39(0.35)	51.10(0.35)	52.11(0.36)	52.04(0.36)	52.83(0.37)

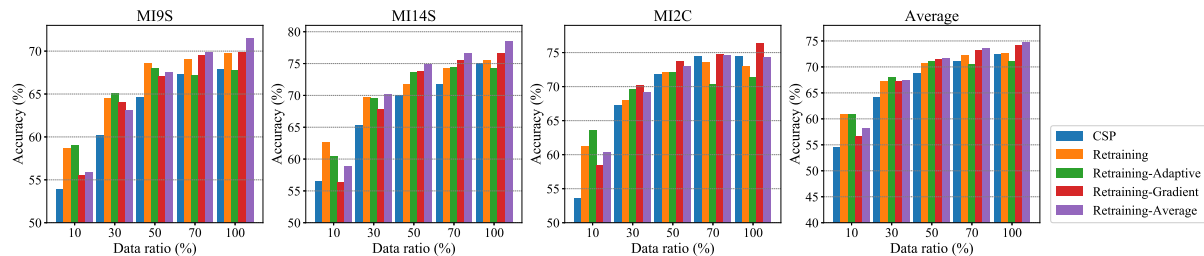


Figure B2 Classification accuracies of different ensemble strategies.

Table B7 Classification accuracies (%) and kappa values of DNN models and retraining with different data ratios. The highest accuracies on each dataset are marked in bold.

Dataset	Scenario	Approach	Data ratio					
			10	20	30	40	50	100
MI9S	Within-Subject	EEGNet	57.30(0.14)	63.66(0.27)	65.02(0.29)	64.28(0.28)	66.47(0.32)	71.63(0.43)
		DeepCNN	52.05(0.04)	53.55(0.07)	54.03(0.07)	56.11(0.12)	56.50(0.12)	59.33(0.18)
		ShallowCNN	57.14(0.14)	60.93(0.21)	63.64(0.26)	63.23(0.26)	65.21(0.30)	70.93(0.41)
		CNN+LSTM	50.49(0.01)	53.47(0.07)	55.12(0.10)	56.50(0.13)	57.76(0.15)	65.44(0.30)
		LMDANet	51.10(0.02)	58.29(0.16)	57.12(0.14)	60.58(0.21)	64.34(0.28)	65.42(0.30)
		FBCSP-Retraining	59.80(0.19)	65.39(0.30)	67.06(0.34)	68.51(0.36)	68.80(0.37)	73.15(0.46)
	Cross-Subject	EEGNet	56.93(0.14)	59.83(0.20)	61.91(0.24)	61.82(0.24)	62.30(0.25)	63.16(0.26)
		DeepCNN	53.32(0.07)	55.51(0.11)	55.63(0.11)	57.00(0.14)	56.94(0.14)	55.11(0.10)
		ShallowCNN	59.21(0.18)	62.30(0.25)	62.86(0.26)	62.34(0.25)	60.94(0.22)	58.26(0.17)
		CNN+LSTM	51.97(0.04)	56.43(0.13)	60.24(0.20)	63.18(0.26)	63.43(0.27)	66.18(0.32)
		LMDANet	58.82(0.18)	61.66(0.23)	60.88(0.22)	61.32(0.23)	61.77(0.24)	63.41(0.27)
		FBCSP-Retraining	64.63(0.29)	65.26(0.31)	66.27(0.33)	66.26(0.33)	66.79(0.34)	66.98(0.34)
MI14S	Within-Subject	EEGNet	57.38(0.14)	67.27(0.34)	67.66(0.34)	68.53(0.36)	69.83(0.39)	76.57(0.53)
		DeepCNN	50.25(0.00)	52.39(0.04)	51.83(0.03)	52.87(0.05)	54.74(0.09)	57.11(0.14)
		ShallowCNN	52.98(0.06)	58.19(0.16)	61.43(0.22)	65.71(0.31)	69.16(0.37)	73.56(0.46)
		CNN+LSTM	50.91(0.02)	51.41(0.02)	51.66(0.03)	53.52(0.07)	55.15(0.10)	62.21(0.24)
		LMDANet	51.93(0.04)	52.64(0.06)	56.63(0.13)	59.12(0.18)	60.16(0.19)	66.77(0.33)
		FBCSP-Retraining	58.76(0.17)	64.60(0.29)	68.07(0.36)	69.59(0.39)	70.13(0.40)	73.77(0.47)
	Cross-Subject	EEGNet	65.69(0.31)	69.29(0.39)	68.76(0.38)	69.66(0.39)	71.63(0.43)	72.97(0.46)
		DeepCNN	53.01(0.06)	57.69(0.15)	59.16(0.18)	62.23(0.24)	61.94(0.24)	61.20(0.22)
		ShallowCNN	66.11(0.32)	69.73(0.39)	69.34(0.39)	68.67(0.37)	68.39(0.37)	71.20(0.42)
		CNN+LSTM	51.96(0.04)	58.44(0.17)	66.74(0.33)	70.44(0.41)	69.57(0.39)	72.37(0.45)
		LMDANet	64.59(0.29)	66.47(0.33)	68.34(0.37)	68.80(0.38)	66.83(0.34)	67.87(0.36)
		FBCSP-Retraining	71.26(0.43)	74.99(0.50)	76.59(0.53)	77.43(0.55)	77.54(0.55)	77.70(0.55)
MI2C	Within-Subject	EEGNet	61.66(0.23)	64.13(0.28)	67.58(0.35)	69.88(0.39)	70.23(0.40)	74.10(0.48)
		DeepCNN	51.22(0.02)	52.84(0.06)	52.18(0.04)	52.37(0.05)	52.90(0.06)	61.01(0.22)
		ShallowCNN	63.36(0.27)	66.05(0.32)	68.41(0.36)	69.63(0.39)	71.69(0.43)	76.03(0.52)
		CNN+LSTM	50.19(0.01)	51.39(0.03)	52.58(0.05)	54.23(0.09)	57.32(0.15)	62.33(0.24)
		LMDANet	52.75(0.06)	56.51(0.13)	57.88(0.15)	62.00(0.23)	65.35(0.30)	68.98(0.37)
		FBCSP-Retraining	60.66(0.21)	64.14(0.28)	68.01(0.36)	70.24(0.40)	73.07(0.46)	77.61(0.55)
	Cross-Subject	EEGNet	59.46(0.19)	64.74(0.29)	65.62(0.31)	67.16(0.34)	68.09(0.36)	72.38(0.45)
		DeepCNN	51.85(0.04)	60.82(0.22)	66.65(0.33)	68.41(0.37)	68.53(0.37)	71.47(0.43)
		ShallowCNN	62.09(0.24)	64.29(0.29)	66.51(0.33)	68.64(0.37)	68.56(0.37)	73.53(0.47)
		CNN+LSTM	52.25(0.05)	58.18(0.16)	60.59(0.21)	65.63(0.31)	66.68(0.33)	70.31(0.41)
		LMDANet	63.43(0.27)	66.23(0.32)	67.53(0.35)	67.70(0.35)	68.92(0.38)	69.10(0.38)
		FBCSP-Retraining	70.05(0.40)	70.08(0.40)	73.04(0.46)	73.12(0.46)	74.24(0.48)	75.46(0.51)
MI4C	Within-Subject	EEGNet	37.40(0.17)	44.34(0.25)	47.95(0.30)	52.03(0.36)	56.85(0.42)	65.64(0.54)
		DeepCNN	27.51(0.04)	29.05(0.05)	30.55(0.07)	32.66(0.10)	32.34(0.09)	51.10(0.34)
		ShallowCNN	38.59(0.18)	45.16(0.26)	46.39(0.28)	53.02(0.37)	55.91(0.41)	60.89(0.48)
		CNN+LSTM	27.26(0.03)	28.16(0.05)	30.17(0.07)	33.33(0.11)	36.18(0.15)	41.49(0.22)
		LMDANet	30.33(0.08)	35.62(0.13)	40.10(0.20)	40.74(0.20)	44.24(0.26)	50.82(0.35)
		FBCSP-Retraining	44.07(0.25)	49.28(0.31)	53.69(0.37)	56.85(0.42)	60.53(0.47)	66.46(0.55)
	Cross-Subject	EEGNet	35.76(0.14)	41.74(0.22)	44.40(0.26)	46.11(0.28)	47.07(0.29)	50.35(0.34)
		DeepCNN	32.34(0.10)	36.44(0.15)	38.49(0.18)	40.12(0.20)	40.63(0.21)	45.40(0.27)
		ShallowCNN	38.45(0.18)	44.32(0.26)	46.33(0.28)	47.29(0.30)	48.25(0.31)	50.79(0.34)
		CNN+LSTM	33.35(0.11)	36.53(0.15)	37.29(0.16)	38.50(0.18)	38.86(0.18)	39.21(0.19)
		LMDANet	39.61(0.19)	42.92(0.24)	44.85(0.26)	45.75(0.28)	46.46(0.29)	48.28(0.31)
		FBCSP-Retraining	48.19(0.31)	51.39(0.35)	51.10(0.35)	52.11(0.36)	52.04(0.36)	52.83(0.37)

Table B8 Ablation study results. The highest accuracies are marked in bold.

Scenario	Approach	MI9S	MI14S	MI2C	MI4C	Average acc
Within-Subject	CSP-LR	60.16	65.32	67.27	47.48	60.06
	CSP-Retraining-Rand	62.59	68.13	66.52	46.59	60.96
	CSP-Retraining-Fix f	60.67	67.04	69.22	48.49	61.36
	CSP-Retraining	64.53	69.68	67.89	53.14	63.81
Cross-Subject	CSP-LR	53.89	60.04	60.04	36.88	52.71
	CSP-Retraining-Rand	54.73	63.31	55.63	34.04	51.93
	CSP-Retraining-Fix f	53.43	60.44	61.96	38.41	53.56
	CSP-Retraining	54.79	65.21	64.24	43.14	56.85

Table B9 Influence of the number of spatial filters on the classification accuracy.

Scenario	# Filters	Approach	MI9S	MI14S	MI2C	MI4C	Average acc
Within-Subject	4	CSP-LR	60.02	63.53	66.41	42.56	58.13
		CSP-Retraining	62.13	70.02	67.62	49.67	62.36
	8	CSP-LR	60.16	65.32	67.27	47.48	60.06
		CSP-Retraining	64.53	69.68	67.89	53.14	63.81
	12	CSP-LR	62.01	64.59	68.23	47.93	60.69
		CSP-Retraining	64.65	70.23	67.35	54.34	64.14
Cross-Subject	4	CSP-LR	52.80	60.62	59.51	34.43	51.84
		CSP-Retraining	54.62	66.66	64.65	42.21	57.04
	8	CSP-LR	53.89	60.04	60.04	36.88	52.71
		CSP-Retraining	54.79	65.21	64.24	43.14	56.85
	12	CSP-LR	53.31	60.12	60.89	36.17	52.62
		CSP-Retraining	54.83	65.04	63.67	40.01	55.89

Table B10 Influence of the number of frequency bands on the classification accuracy.

Scenario	# Frequency bands	Approach	MI9S	MI14S	MI2C	MI4C	Average acc
Within-Subject	2	FBCSP-LR	64.05	65.99	67.44	50.50	62.00
		FBCSP-Retraining	67.06	68.07	68.01	53.69	64.21
	4	FBCSP-LR	62.66	64.77	68.52	51.82	61.94
		FBCSP-Retraining	65.45	66.91	70.13	54.41	64.23
	6	FBCSP-LR	61.47	64.05	62.68	52.01	60.05
		FBCSP-Retraining	66.44	66.34	66.16	54.04	63.25
Cross-Subject	2	FBCSP-LR	56.32	65.74	64.99	42.24	57.32
		FBCSP-Retraining	58.90	68.07	65.80	43.50	59.07
	4	FBCSP-LR	54.84	63.07	63.56	41.94	55.85
		FBCSP-Retraining	56.74	66.10	64.09	42.42	57.34
	6	FBCSP-LR	55.87	62.53	61.30	40.49	55.05
		FBCSP-Retraining	57.32	64.66	62.75	41.65	56.60

- 6 Reuderink B, Poel M. Robustness of the common spatial patterns algorithm in the BCI-pipeline. University of Twente, The Netherlands, Technical Report. 2008
- 7 Blankertz B, Kawanabe M, Tomioka R, et al. Invariant common spatial patterns: Alleviating nonstationarities in brain-computer interfacing. *Adv Neural Inf Process Syst*, 2007, 20: 113–120
- 8 Lu H, Plataniotis K N, Venetsanopoulos A N. Regularized common spatial patterns with generic learning for EEG signal classification. In: *Proceedings of Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Minneapolis, MN, 2009. 6599–6602
- 9 Kang H, Nam Y, Choi S. Composite common spatial pattern for subject-to-subject transfer. *IEEE Signal Process Lett*, 2009, 16: 683–686
- 10 Yong X, Ward R K, Birchard G E. Sparse spatial filter optimization for EEG channel reduction in brain-computer interface. In: *Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing*, Las Vegas, NV, 2008. 417–420
- 11 Novi Q, Guan C T, Dat T H, et al. Sub-band common spatial pattern (SBCSP) for brain-computer interface. In: *Proceedings of International IEEE/EMBS Conference on Neural Engineering*, Kohala Coast, HI, 2007. 204–207
- 12 Ang K K, Chin Z Y, Zhang H, et al. Filter bank common spatial pattern (FBCSP) in brain-computer interface. In: *Proceedings of the International Joint Conference on Neural Networks*, Hong Kong, China, 2008. 2390–2397
- 13 Faller J, Vidaurre C, Solis-Escalante T, et al. Autocalibration and recurrent adaptation: Towards a plug and play online ERD-BCI. *IEEE Trans Neural Syst Rehabil Eng*, 2012, 20: 313–319
- 14 Xia K, Deng L, Duch W, et al. Privacy-preserving domain adaptation for motor imagery-based brain-computer interfaces. *IEEE Trans Biomed Eng*, 2022, 69: 3365–3376
- 15 Jayaram V, Barachant A. MOABB: trustworthy algorithm benchmarking for BCIs. *J Neural Eng*, 2018, 15: 066011
- 16 Long M S, Cao Y, Cao Z J, et al. Transferable representation learning with deep adaptation networks. *IEEE Trans Pattern Anal Mach Intell*, 2019, 41: 3071–3085
- 17 Long M S, Cao Z J, Wang J M, et al. Conditional adversarial domain adaptation. *Adv Neural Inf Process Syst*, 2018, 31: 1640–1650
- 18 Jin Y, Wang X M, Long M S. Minimum class confusion for versatile domain adaptation. In: *Proceedings of European Conference on Computer Vision*, Glasgow, UK, 2020. 464–480
- 19 Lawhern V J, Solon A J, Waytowich N R, et al. EEGNet: a compact convolutional neural network for EEG-based brain-computer interfaces. *J Neural Eng*, 15: 056013
- 20 Schirrmester R T, Springenberg J T, Fiederer L D J, et al. Deep learning with convolutional neural networks for EEG decoding and visualization. *Hum Brain Mapp*, 2017, 38: 5391–5420
- 21 Zhang R L, Zong Q, Dou L Q, et al. Hybrid deep neural network using transfer learning for EEG motor imagery decoding. *Biomed Signal Process Control*, 2021, 63: 102144
- 22 Miao Z Q, Zhao M R, Zhang X, et al. LMDA-Net: A lightweight multi-dimensional attention network for general EEG-based brain-computer interfaces and interpretability. *NeuroImage*, 2023, 276: 120209
- 23 Freund Y, Schapire R E. Experiments with a new boosting algorithm. In: *Proceedings of International Conference on Machine Learning*, Bari, Italy, 1996. 148–156
- 24 Friedman J H. Greedy function approximation: a gradient boosting machine. *Ann Stat*, 2001, 29: 1189–1232