

Effects of High-Frequency Transcranial Random Noise Stimulation on a Motor Imagery–Steady-State Visual Evoked Potential Hybrid Brain–Computer Interface

Yichun Wang¹, Meng Gu¹, Yuhuan Zhang¹, Xiaorong Gao (✉)², Xiaogang Chen (✉)¹

¹ State Key Laboratory of Advanced Medical Materials and Devices, Institute of Biomedical Engineering, Tianjin Institutes of Health Science, Chinese Academy of Medical Sciences and Peking Union Medical College, Tianjin 300192, China

² School of Biomedical Engineering, Tsinghua University, Beijing 100084, China

© The Author(s) 2026. This article is published by Higher Education Press.

ABSTRACT High-frequency transcranial random noise stimulation (tRNS) can modulate cortical excitability, but its effects on hybrid brain–computer interfaces (BCIs) remain unclear. We used a sham-controlled, within-subject crossover design to evaluate a hybrid BCI combining motor imagery (MI) and steady-state visual evoked potentials (SSVEPs) in 24 healthy adults. Participants performed the task before and after either Cz–Fpz tRNS or sham stimulation. SSVEP decoding was performed using ensemble task-related component analysis (eTRCA), whereas MI decoding used a regularized filter-bank common spatial pattern (FBCSP) framework with a radial-basis-function support vector machine (RBF-SVM). Classifier outputs were combined using adaptive decision-level weighting. The task elicited frequency-specific SSVEP responses and MI-related sensorimotor activity under both stimulation conditions. Following active tRNS, MI decoding accuracy increased significantly by 6.33–8.29 percentage points for cumulative windows ending between 3 and 5 s. In contrast, between-condition differences in SSVEP and hybrid decoding were not significant. Exploratory spectral analyses further showed significant post-intervention increases in mu-band power during both the baseline and task periods after active tRNS. Consistent with this pattern, group-level event-related desynchronization (ERD) values showed a descriptive shift towards stronger desynchronization following active stimulation, although this change did not reach statistical significance. These findings characterize complementary neural responses and decoding performance in a hybrid task, with within-session MI improvement following active tRNS but no demonstrated advantage over sham.

KEYWORDS Brain–computer interface; Motor imagery; Steady-state visual evoked potential; Electroencephalography; Transcranial random noise stimulation

1 Introduction

Brain–computer interfaces (BCIs) translate brain activity into commands or feedback for external devices, enabling assistive control and neurorehabilitation in people with motor impairment [1–3]. Among noninvasive approaches, electroencephalography (EEG)-based motor imagery (MI) and steady-state visual evoked potentials (SSVEP) paradigms provide complementary control signals. MI engages sensorimotor networks without overt movement, making it relevant to rehabilitation training [4]. However, its substantial interindividual variability can limit decoding reliability [5]. SSVEP-based BCIs use frequency-locked visual responses to support accurate decoding with relatively little training [6,7], although

sustained flicker can cause discomfort and fatigue, particularly at low or intermediate frequencies [8].

Hybrid BCIs combine the endogenous activity associated with MI and the frequency-specific responses elicited by SSVEP stimulation. In this task, MI encodes the cued hand movement, while high-frequency visual stimulation tags the attended target. Combining these signals may improve decoding reliability while preserving active MI, an important component of rehabilitation-oriented training. Previous work has explored hybrid BCIs for decoding and control applications [9,10], including hand MI combined with peripheral high-frequency SSVEP stimulation [11]. Stimulus frequency, modulation depth, and spatial arrangement are also relevant because they influence both

Received 22 Jun 2026; accepted 17 Sep 2026

E-mails: gxr-dea@tsinghua.edu.cn (Gao X.),
chenxg@bme.cams.cn (Chen X.).

visual comfort and neural responses [8,11,12].

Neuromodulation may influence the endogenous and exogenous components of a hybrid BCI differently. Transcranial electrical stimulation (tES) can influence cortical excitability, neural oscillatory activity, or task-related network states through weak electrical currents [13], and stimulation frequency may shape motor-learning-related effects [14]. Previous MI-BCI studies have mainly focused on transcranial direct current stimulation (tDCS), including work combining tDCS with MI-BCI or robotic feedback for stroke rehabilitation [15,16]. Recent meta-analytic evidence on MI combined with non-invasive central or peripheral stimulation indicates that rehabilitation effects remain heterogeneous and depend on protocol, patient characteristics, and whether BCI technology is used [17]. Transcranial alternating current stimulation (tACS) has also attracted attention because it can target endogenous sensorimotor rhythms; recent work has reported that tACS can improve the performance of MI-SSVEP hybrid BCI systems under some conditions [18,19]. Thus, current BCI neuromodulation research has largely emphasized tDCS and tACS, whereas the role of transcranial random noise stimulation (tRNS) in hybrid BCIs remains less well characterized.

tRNS applies randomly fluctuating currents over a specified frequency range. Terney et al. reported increased corticospinal excitability after high-frequency stimulation of the primary motor cortex, with effects associated with the 100–640 Hz range [20]. Proposed mechanisms include modulation of membrane-potential dynamics and stochastic resonance [13,21–23]. Reviews suggest potential effects on motor excitability and behavior that depend on stimulation parameters, cortical target, task state, and baseline performance [22–24]. Resting-state EEG findings have been less consistent [25], whereas early clinical studies combining tRNS with functional practice have reported promising upper-limb outcomes after stroke [26]. Together, these observations motivate investigation of tRNS during rehabilitation-oriented BCI use, while leaving its effects on the constituent signals and their combined output unresolved.

A Cz–Fpz montage offers a means of examining tRNS in a bilateral hand-MI task. Because changes in an individual component need not translate directly into improved hybrid decoding, we assessed MI and SSVEP responses alongside the fused output.

We used a sham-controlled, within-subject crossover design to evaluate 100–640 Hz tRNS delivered between two MI-SSVEP task phases. We characterized frequency-specific visual and sensorimotor responses, assessed MI, SSVEP, and fusion decoding, and compared pre-to-post

changes between active tRNS and sham. Signal-to-noise ratio (SNR), inter-trial phase coherence (ITPC), and contralateral region-of-interest (ROI) event-related desynchronization (ERD) were used to examine neural changes alongside decoding performance.

2 Materials and Methods

2.1 Participants

Twenty-four healthy adult volunteers were recruited through public announcements and completed the protocol; all were included in the analysis (11 males and 13 females; mean age, 23.78 years; range, 22–27 years). All participants were right-handed and had normal or corrected-to-normal vision. None had a history of neurological or psychiatric disorders, intracranial or implanted metallic devices, epilepsy, or photosensitivity, and none had previously received tES. All participants provided written informed consent. This study was approved by the Ethics Review Committee for Life Science and Medical Research Involving Humans, Institute of Biomedical Engineering, Chinese Academy of Medical Sciences (No. L2025-045-001).

2.2 Design overview

The study used a single-blind, sham-controlled, within-subject crossover design. EEG was recorded with a 64-channel cap, and stimulation electrodes were positioned at Cz and Fpz (Fig. 1A). Each participant completed active-tRNS and sham sessions, each comprising five pre-intervention task blocks, a 20 min intervention, and five post-intervention blocks (Fig. 1B). Sessions were separated by at least 7 days. Participants were unaware of the stimulation condition; the experimenter administering stimulation was not blinded.

The intersession interval exceeded the approximately 40–60 min duration reported for acute changes in cortical excitability after high-frequency tRNS [20,27].

2.3 Hybrid BCI task

The hybrid BCI task combined hand MI with frequency-specific visual stimulation [28]. MI is associated with ERD and event-related synchronization (ERS) of sensorimotor mu and beta rhythms [4,29], whereas SSVEP stimulation elicits frequency-locked responses over visual cortex [6,7].

Task cues were presented on a 24-inch liquid-crystal display with a refresh rate of 120 Hz and a resolution of 1920 × 1080 pixels, approximately 70 cm from the eyes.

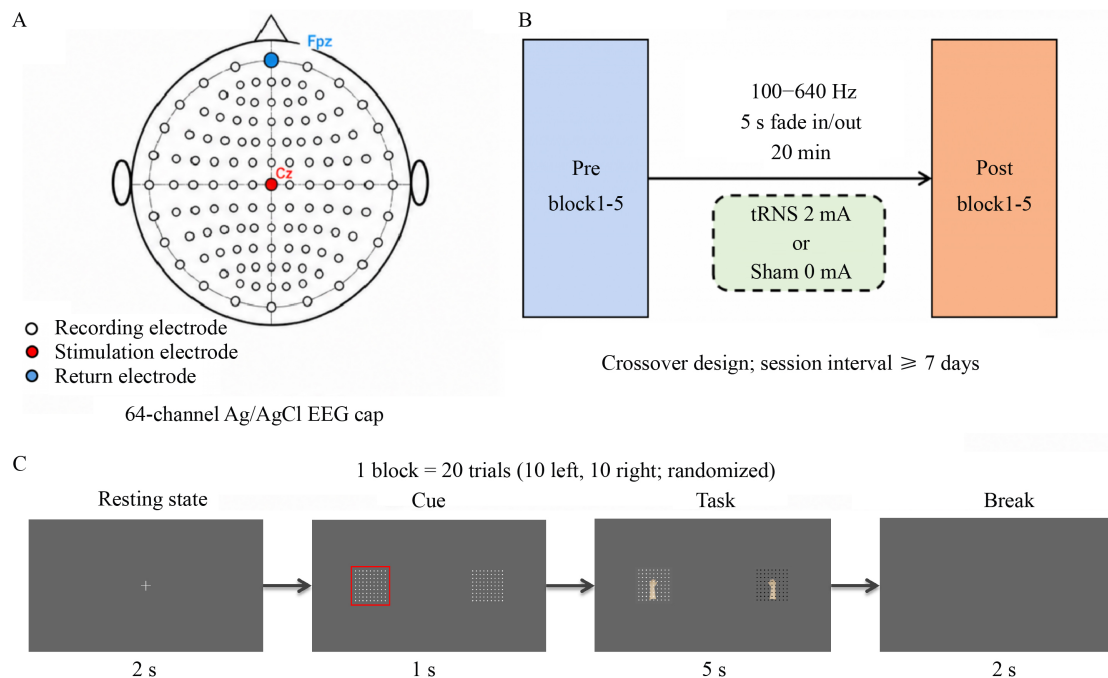


Fig. 1 Study design and hybrid BCI task procedure. The study used a sham-controlled, within-subject crossover design. (A) EEG was recorded using a 64-channel Ag/AgCl electrode cap; one tRNS electrode was placed at Cz and the other at Fpz. (B) Each participant completed both tRNS and sham sessions, with an intersession interval of at least 7 days. Each session consisted of five pre-intervention blocks, a 20 min stimulation intervention, and five post-intervention blocks. Active stimulation consisted of 100–640 Hz, 2 mA high-frequency tRNS; sham stimulation used the same electrode montage, but current was delivered only briefly before being ramped down to 0 mA. (C) Each trial lasted 10 s and consisted sequentially of 2 s rest, 1 s cue, 5 s concurrent MI-SSVEP task, and 2 s rest. Each block included 20 randomized trials, with 10 left-target and 10 right-target trials.

Peripheral point-like stimuli on the left and right flickered at 34 and 35 Hz, respectively, at an eccentricity of approximately 2.5 degrees relative to the central fixation point. Participants attended to the cued animation region rather than directly fixating the flickering dots. This arrangement was intended to reduce visual fatigue while retaining peripheral high-frequency stimulation [8,12,30,31]. The stimulation frequencies were separated from the bands used for MI analysis.

EEG signals were recorded using a NeuroScan SynAmps2 system. All participants wore a 64-channel Ag/AgCl electrode cap, with electrode positions following the extended 10-20 system. Signals were sampled at 1000 Hz with a hardware filter range of 0.1–200 Hz. Electrode impedances were maintained below 20 k Ω .

Each trial comprised 2 s rest, a 1 s directional cue, a 5 s joint MI-SSVEP task, and 2 s intertrial rest (Fig. 1C). During the initial rest, participants relaxed and fixated a central cross. A red-framed cue indicated the left or right target, and the corresponding peripheral stimulus began to flicker. EEG event codes 1 and 2 marked the subsequent onset of the joint MI-SSVEP task, defined as time zero; the cue interval therefore occupied -1 to 0 s. During the task, participants performed kinesthetic MI of

the cued hand while looking at the corresponding animation region. Instructions emphasized imagining the proprioceptive sensation of movement rather than merely visualizing it [32]. The screen was blank during the final rest interval.

Each block contained 20 trials, comprising 10 left-hand and 10 right-hand trials presented in randomized order. The five post-intervention blocks began immediately after stimulation and followed the same structure as the five pre-intervention blocks.

Participants received standardized instructions and a brief practice session to familiarize themselves with MI and the visual task. The experiment was open-loop, without online feedback.

2.4 tRNS and sham stimulation protocol

tRNS was delivered using a NeuroConn DC-Stimulator PLUS (NeuroConn GmbH, Germany). The waveform comprised zero-mean Gaussian-distributed random noise at 100–640 Hz, a high-frequency range associated with changes in cortical excitability [33]. Peak current was 2 mA, and stimulation lasted 20 min, with linear 5 s ramp-up and ramp-down periods intended to reduce cutaneous discomfort and support participant blinding.

Two saline-soaked sponge electrodes were used to deliver tRNS. The target electrode was centered over Cz ($7\text{ cm} \times 5\text{ cm}$, area 35 cm^2), and the return electrode was centered over Fpz ($7\text{ cm} \times 5\text{ cm}$, area 35 cm^2). This Cz–Fpz montage yielded an estimated current density of approximately 0.057 mA/cm^2 at each electrode, within commonly used safety limits for low-intensity tES [27,34].

The Cz–Fpz montage was selected to target midline sensorimotor regions relevant to bilateral hand MI. A midline configuration was chosen instead of unilateral C3 or C4 stimulation to avoid preferentially targeting one hemisphere.

Sham stimulation used the same montage, device connection, and ramp settings. Current initially rose to the target intensity, then decreased to 0 mA and was discontinued, while the device displayed the full 20 min countdown. This procedure was intended to reproduce the initial cutaneous sensation without prolonged stimulation.

2.5 EEG preprocessing

EEG was preprocessed in MATLAB using EEGLAB (v2025.1.0) [35], with the same pipeline applied across participants, conditions, and phases. Reference, ground, and other non-scalp channels were removed from the 64-channel recordings, leaving 60 scalp EEG channels. Retained channel names were matched to a standard electrode-location template.

Continuous EEG was downsampled to 250 Hz, band-pass filtered at 0.5–100 Hz, and notch filtered at 50 Hz ($\pm 2\text{ Hz}$). Filter design aimed to minimize phase distortion and edge artifacts [36].

Bad channels were identified automatically using channel standard deviation, peak-to-peak range, high-frequency power proportion, and interchannel correlation. Channels that deviated markedly from the overall distribution were reconstructed using spherical spline interpolation [37].

After channel interpolation, EEG was rereferenced to the channel average. Valid blocks from each participant and phase were concatenated for independent component analysis (ICA). Extended Infomax ICA was applied when the concatenated data exceeded 30 s [38]. ICLabel classified the resulting components [39]; components assigned to non-brain sources with probability > 0.70 were removed, including ocular, muscle, line-noise, and channel-noise components. If ICLabel was unavailable or failed, abnormal components were identified using a kurtosis-based fallback procedure.

The preprocessed continuous data were epoched using EEG event codes 1 and 2, which marked the onset of the

joint MI-SSVEP task. Epochs extended from -3 to $+7\text{ s}$ relative to this task onset. Segments with insufficient length, incomplete event markers, or obvious residual artifacts were excluded. The -3 to -1 s interval, preceding the directional cue, was used for baseline correction. The subsequent cue interval (-1 to 0 s) was excluded from the baseline.

2.6 Signal analysis

2.6.1 SSVEP processing

The overall signal-analysis and fusion pipeline is shown in Fig. 2. SSVEP SNR and ITPC were assessed over nine parieto-occipital electrodes: Pz, PO7, PO3, POz, PO4, PO8, O1, Oz, and O2. The channel set used for SSVEP decoding is specified below.

EEG segments from 0 to 5 s after joint-task onset were demeaned, multiplied by a Hann window, and transformed using a 2500-point fast Fourier transform (FFT). Spectra were calculated separately for each intervention phase, stimulation condition, and target frequency. SSVEP SNR was calculated in decibels as ten times the base-10 logarithm of the ratio of target-frequency power to the mean power of neighboring FFT bins located 0.3–0.7 Hz below and above the target frequency. Power spectra were averaged across trials before calculation of this ratio. ITPC was calculated as the magnitude of the mean unit-length complex phase vector across trials at each target FFT frequency and ranged from 0 to 1, with higher values indicating greater trial-to-trial phase consistency. SNR and ITPC were computed separately for each participant, channel, target frequency, intervention phase, and stimulation condition.

For SSVEP decoding, multiple cumulative data-window endpoints from 0.5 to 5 s after joint-task onset were evaluated to characterize the dependence of classification performance on data length. Classification was performed using ensemble task-related component analysis (eTRCA) [40]. Signals were processed using a two-subband filter bank consisting of Chebyshev type-I band-pass filters with passbands of 32–90 Hz and 66–90 Hz. The corresponding stopband edges were 26 and 100 Hz for the first subband and 60 and 100 Hz for the second subband. Zero-phase filtering was applied to both subbands.

Five-fold block-wise cross-validation was used. In each fold, four blocks were used to construct the eTRCA spatial filters and class templates, while the remaining block was used for testing. Based on a preliminary parameter-sensitivity analysis, classification scores from the two subbands were combined using fixed weights of 0.7 and 0.3 for the first and second subbands,

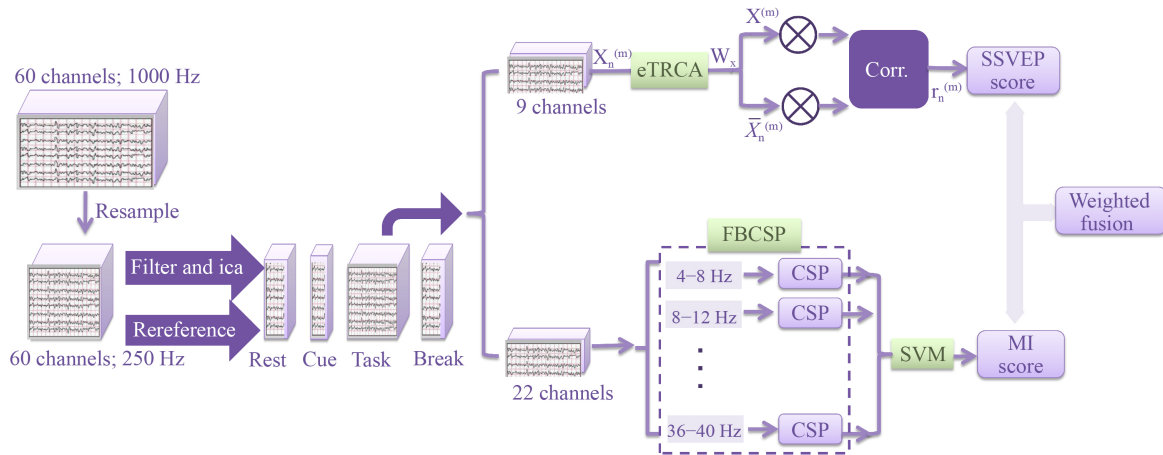


Fig. 2 Signal-analysis and fusion pipeline for the MI-SSVEP hybrid BCI. After removal of non-scalp/reference channels, the retained 60-channel EEG signals were downsampled, filtered, cleaned, rereferenced, and epoched before entering component-specific decoding branches. The SSVEP branch used nine parieto-occipital channels and filter-bank eTRCA to obtain normalized SSVEP scores. The MI branch used 12 channels selected from a pool of 22 candidate EEG channels, regularized FBCSP, and an RBF-SVM to obtain normalized MI scores. The two score streams were then combined by adaptive weighted decision-level fusion to generate the final fused command and decoding accuracy.

respectively. The same channel set, filter-bank settings, and subband weights were applied to both stimulation conditions. Spatial filters and class templates were fitted independently for the pre- and post-intervention phases.

2.6.2 MI processing

MI-related neural activity was quantified using band-limited ERD and synchronization (ERD/ERS) and absolute power spectral density (PSD). EEG signals were re-referenced to the common average and epoched relative to joint-task onset. For each trial and electrode, spectral power was estimated separately during a baseline interval (−3 to −1 s) and a task interval (0–5 s). ERD/ERS was expressed as the percentage change in task-related power relative to baseline according to Eq. (1).

$$\text{ERD/ERS(\%)} = 100 \times \frac{P_{\text{task}} - P_{\text{baseline}}}{P_{\text{baseline}}} \quad (1)$$

where P_{task} and P_{baseline} denote band-limited power during the task and baseline intervals, respectively. Trial-level estimates were averaged within each participant, imagined hand, stimulation condition, intervention phase, and electrode before group-level analysis. Because percentage-based estimates of ERD may be disproportionately influenced by variability in baseline power [41], potential outliers were additionally considered. For each paired pre-post comparison, participant-level change scores were calculated, and outliers were identified using Tukey's rule [42,43]. Specifically, change scores falling below the first quartile minus 1.5 times the interquartile range ($Q1 - 1.5 \times \text{IQR}$) or above the third quartile plus 1.5 times the interquartile

range ($Q3 + 1.5 \times \text{IQR}$) were classified as outliers.

Sensorimotor activity was summarized within bilateral nine-electrode regions of interest (ROIs). The left-hemisphere ROI comprised FC5, FC3, FC1, C5, C3, C1, CP5, CP3, and CP1, whereas the right-hemisphere ROI comprised FC2, FC4, FC6, C2, C4, C6, CP2, CP4, and CP6. ROIs were designated as contralateral or ipsilateral according to the imagined hand. Electrode-level values were averaged within each participant to obtain a single ROI-level estimate for each condition and intervention phase. Absolute PSD was estimated using Welch's method over the same baseline and task intervals for the predefined mu (8–13 Hz) band. Spectral power was then averaged across the corresponding frequency range and electrodes within each ROI.

MI decoding was performed using a regularized filter-bank common spatial pattern (FBCSP) framework [44,45]. The candidate channel pool comprised 22 centroparietal electrodes: FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP7, CP5, CP3, CP1, CPz, P5, P3, P1, Pz, P2, P4, and P6. Signals were band-pass filtered from 4 to 40 Hz. Classification performance was evaluated using cumulative windows ending at 0.5, 1, ..., and 5 s after joint-task onset. To reduce contributions from cue-evoked visual and transient task-switching responses, the first 0.2 s after task onset was excluded from feature extraction. Thus, classification windows extended from 0.2 s to each corresponding endpoint, yielding effective data durations ranging from 0.3 to 4.8 s.

A preliminary sensitivity analysis of channel number identified a 12-channel configuration that achieved performance comparable to the best-performing configuration while retaining a lower-dimensional feature

representation. Within each outer training fold, the 22 candidate electrodes were ranked according to the mutual information between channel-wise log-variance features and class labels, and the 12 highest-ranked electrodes were selected. Channel ranking was performed using training trials from the full 5-s task interval, and the selected channel set was held fixed across all cumulative window endpoints within that fold. Data from the held-out block were not used for channel selection.

The filter bank comprised nine contiguous 4-Hz subbands spanning 4–40 Hz: 4–8, 8–12, 12–16, 16–20, 20–24, 24–28, 28–32, 32–36, and 36–40 Hz. Within each subband, regularized CSP spatial filters were estimated exclusively from the training data, with three spatial filters retained from each class. CSP covariance matrices were estimated using shrinkage regularization with a shrinkage coefficient of 0.5. The resulting log-variance features were standardized using the mean and standard deviation estimated from the training set and subsequently classified using a radial-basis-function support vector machine (RBF-SVM). The BoxConstraint parameter was selected by inner cross-validation from candidate values of 0.1, 0.5, 1, 2, and 5. Channel selection, CSP estimation, feature standardization, and classifier hyperparameter optimization were performed entirely within the training data before the fitted processing pipeline was applied to the corresponding held-out block.

2.6.3 Fusion decoding

Offline decision-level fusion used five-fold block-wise cross-validation, with four blocks for training and one for testing in each fold. Pre- and post-intervention phases were evaluated independently, without transferring fitted parameters between phases.

The eTRCA module produced class-wise correlation scores, whereas the MI module produced RBF-SVM decision scores. The eTRCA scores were shifted by subtracting the maximum class score within each trial and converted to probability-like scores using a softmax transformation with a fixed scaling coefficient of 3. MI scores were arranged by class; when scores fell outside the interval from -0.5 to 1.5 , a sigmoid transformation with a fixed coefficient of 0.6 was applied. The two MI class scores were then normalized to sum to one. The normalized scores served as comparable inputs to fusion rather than independently calibrated class probabilities. The scaling coefficients (3 for eTRCA and 0.6 for MI) were fixed across the pre- and post-intervention phases and were distinct from the adaptive fusion-weight parameters.

Normalized MI and SSVEP scores were combined by

weighted summation. The trial-wise MI weight depended on the relative classification margins of the two modalities. MI contributed less when its inner-fold performance was low or its prediction conflicted with a more confident SSVEP prediction, and more when its prediction was reliable and concordant.

For each phase and outer fold, MI reliability and adaptive fusion weights were estimated from the training data. The held-out block was used only for evaluation [46,47]. The same fixed score transformations and adaptive weighting procedure were applied before and after stimulation.

Classification accuracy was calculated for each participant, stimulation condition, phase, modality, and cumulative window endpoint. Pre-to-post changes were calculated as post-intervention minus pre-intervention values; stimulation contrasts were the paired active-tRNS minus sham changes.

2.6.4 Statistical analysis

All tests were two-sided and used participants as the unit of analysis, preserving within-participant pairing. Multiple comparisons were controlled using the Benjamini-Hochberg false discovery rate (FDR) procedure within the families specified below [48–50]. Throughout, q denotes an FDR-adjusted p value, with significance defined as $q < 0.05$. Group summaries are reported as mean $\pm$ standard error of the mean (SEM).

Within-condition accuracy changes were tested against zero using paired sign-flip permutation tests. For each decoding modality, the ten cumulative windows (0.5–5 s) in each of the two stimulation conditions formed a 20-test family.

Between-condition differences in accuracy gains were assessed using paired sign-flip permutation tests with 100,000 permutations. The three modalities and ten cumulative window endpoints formed a 30-test family.

ERD comparisons used paired sign-flip permutation tests with 100,000 permutations and unfiltered participant-level values.

3 Results

3.1 SSVEP

Clear spectral peaks were observed at the two stimulation frequencies, 34 and 35 Hz, together with their second harmonics at 68 and 70 Hz, both before and after active tRNS and sham stimulation (Fig. 3A), confirming robust frequency-specific SSVEP responses across intervention phases.

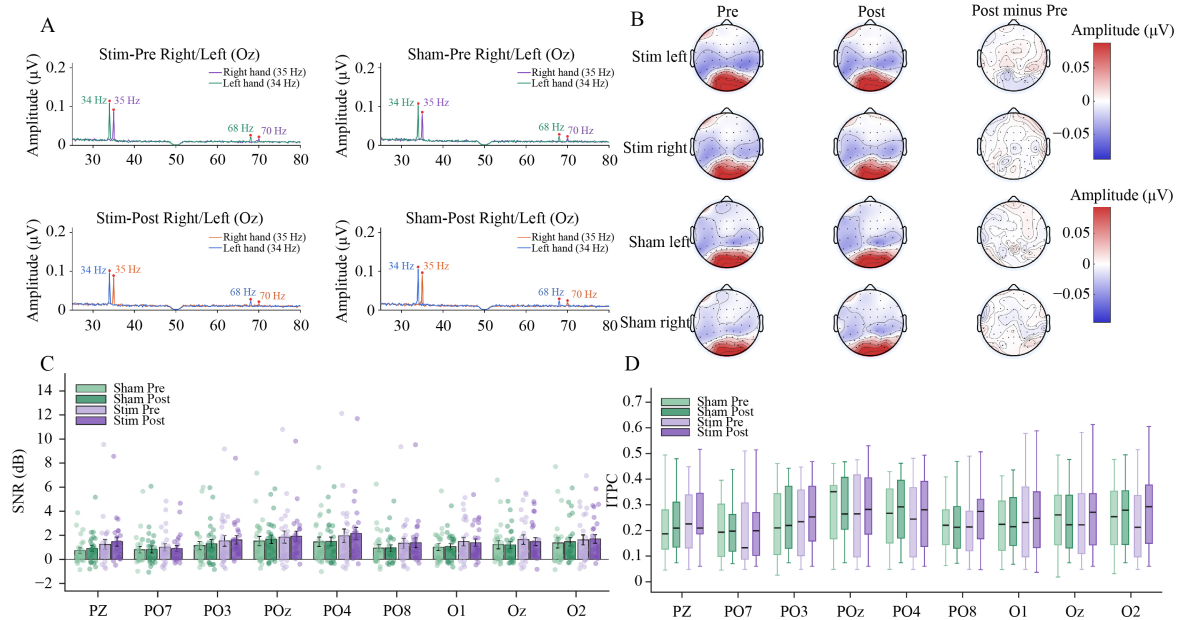


Fig. 3 SSVEP frequency responses, SNR, and phase stability under sham and active stimulation conditions. (A) Mean spectra in the pre and post phases. Spectral distributions around the left and right target stimulation frequencies are shown separately under the active stimulation and sham conditions; 34 Hz and 35 Hz are the primary SSVEP target frequencies. (B) Channel-centered SSVEP amplitude topographies at the target frequency. Rows show active-tRNS left-hand (34 Hz), active-tRNS right-hand (35 Hz), sham left-hand (34 Hz), and sham right-hand (35 Hz) conditions; columns show pre-intervention, post-intervention, and post-minus-pre maps. (C) SSVEP SNR distributions across nine parieto-occipital channels. Bars represent the mean SNR across subjects and error bars indicate the SEM. (D) ITPC distributions over the same channels.

The spatial distributions of the SSVEP responses were further examined using scalp topographies of the 34- and 35-Hz target-frequency amplitudes. For visualization, amplitudes were centered across channels to emphasize their relative spatial distributions rather than absolute amplitude differences. The responses were predominantly distributed over the occipital region under both stimulation conditions, whereas the corresponding post-minus-pre maps showed only relatively small spatial changes following either active tRNS or sham stimulation (Fig. 3B).

SNR and ITPC were subsequently examined over the nine parieto-occipital electrodes. For the channel-wise visualization, the 34- and 35-Hz values were averaged within each participant, whereas the regional summary was obtained by further averaging across the nine electrodes. Both SNR and ITPC showed noticeable variation across channels and participants, but the pre- and post-intervention distributions overlapped substantially under both active tRNS and sham stimulation (Figs. 3C and 3D).

Consistent with these distributions, neither SSVEP SNR nor ITPC showed a significant pre-to-post change under active tRNS or sham stimulation, and the magnitude of the pre-to-post change did not differ significantly between the two stimulation conditions (Figs. 3C and 3D). Thus, although reliable frequency-

locked SSVEP responses were present throughout the experiment, no detectable modulation of response strength or phase consistency was observed following active tRNS.

3.2 MI

Fig. 4A shows the response phenotype of a representative participant under the sham condition, with a lateralized ERD/ERS pattern over the sensorimotor cortex, demonstrating that the present paradigm successfully elicited MI-related features. To further characterize MI-related changes in motor imagery activity, PSD during the baseline and task periods was examined separately. At the group level, active stimulation was associated with sustained post-intervention increases in mu-band PSD during both periods, extending across both ipsilateral and contralateral motor regions (Fig. 4B). In contrast, the sham condition showed only modest pre-to-post changes. Under active tRNS, the increases remained significant after FDR correction during both the baseline period ($q = 0.0369$) and the task period ($q = 0.0387$). Notably, when the baseline- and task-period spectra were displayed using the same y-axis scale, mu-band power was higher during baseline than during motor imagery, and the post-intervention increase appeared greater during the baseline period. Thus, the stimulation-related increase in mu-band

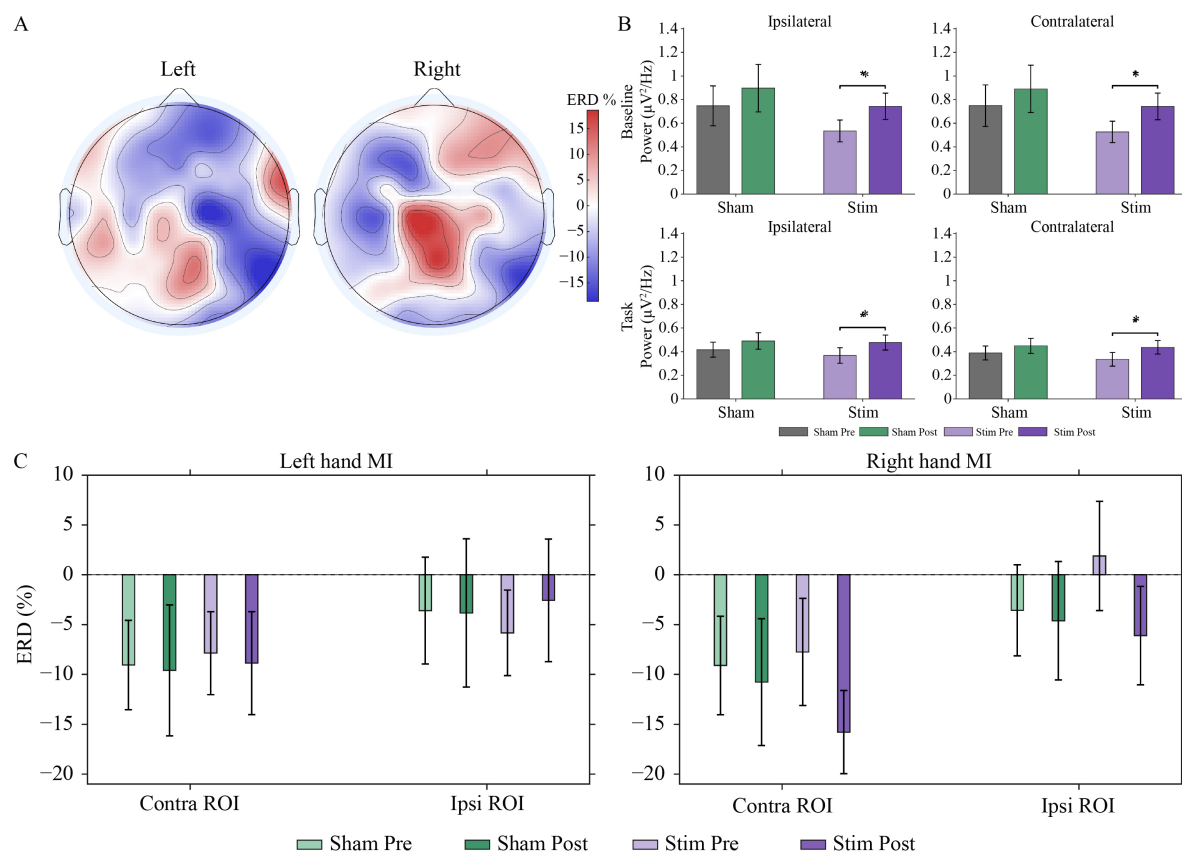


Fig. 4 MI-related mu activity, mu-band PSD and ERD/ERS before and after stimulation. (A) Scalp topography of mu-band ERD/ERS during MI in a representative participant under the sham condition. (B) Group-level mu-band PSD during the baseline period (top row) and task period (bottom row), shown separately for the ipsilateral and contralateral sensorimotor ROIs. Bars represent the mean and error bars indicate the SEM. Asterisks indicate significant paired pre-to-post differences within the corresponding stimulation condition after false-discovery-rate correction ($q < 0.05$). (C) Group-level mu-band ERD/ERS over the contralateral and ipsilateral sensorimotor ROIs during left- and right-hand MI after the fixed exclusion of two participants with extreme values. Bars represent the mean, and error bars indicate the SEM.

power was not confined to task execution but was already evident in the pre-task baseline state.

Because ERD/ERS reflects task-related spectral changes relative to baseline, we next examined the baseline-normalized ERD/ERS response to determine how these differential PSD changes were expressed at the relative level (Fig. 4C). Responses over the contralateral motor cortex were predominantly negative, consistent with task-related mu desynchronization. Following active stimulation, ERD values tended to shift toward more negative values, with the clearest contralateral hemispheric pattern observed during right-hand MI, whereas the corresponding changes under sham stimulation were relatively small. Although the post-stimulation enhancement of ERD did not reach statistical significance, its direction was consistent with the PSD findings. Specifically, the proportional increase in baseline mu power was greater than that during the task period, thereby reducing the task-to-baseline power ratio and producing more negative ERD values. Tukey's rule

identified two participant-level change scores as potentially influential observations. Excluding these observations in the sensitivity analysis did not alter the direction or statistical interpretation of the main findings.

3.3 Classification accuracy

As shown in Figs. 5A and 5B, offline decoding accuracy generally increased with cumulative window length across the 24 participants under both stimulation conditions, consistent with the expected benefit of longer data segments for classification. SSVEP and hybrid decoding were numerically more accurate than MI decoding across most window lengths, indicating that the SSVEP component provided a relatively stable source of discriminative information and likely contributed substantially to the hybrid decoder. Following the intervention, mean decoding accuracy increased at most window endpoints, although the magnitude and direction of individual changes varied considerably across

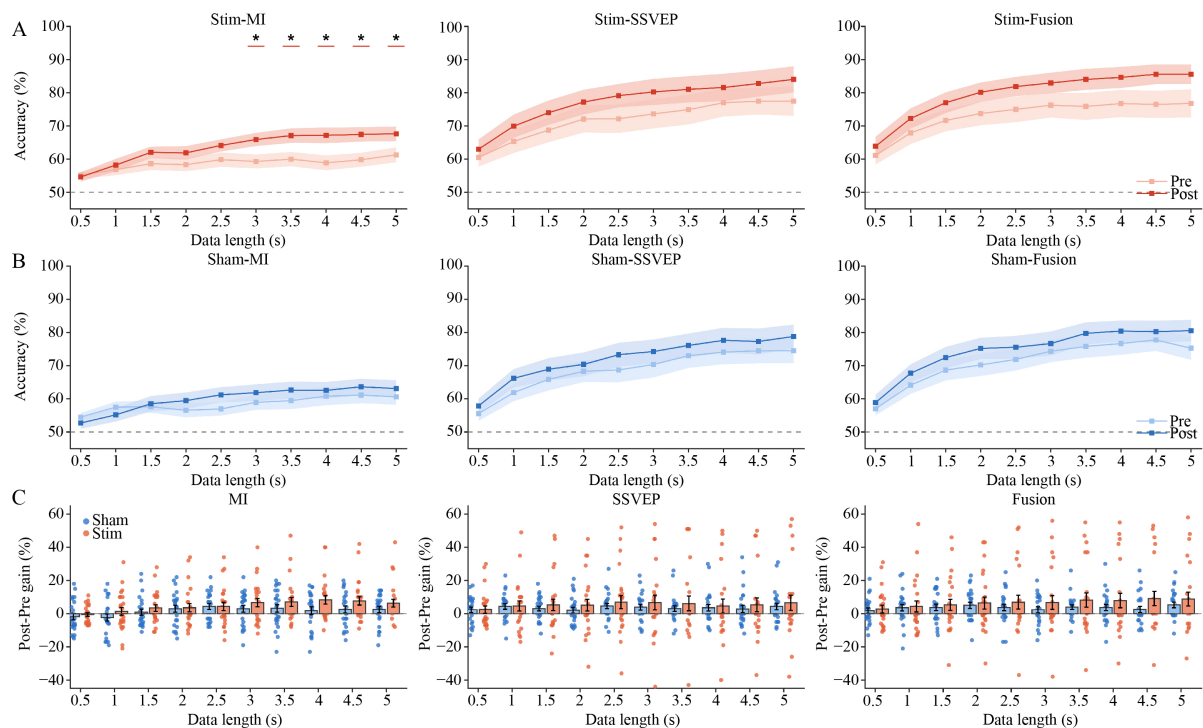


Fig. 5 Classification accuracy and pre-to-post accuracy gain across data lengths. (A) Pre- and post-intervention classification accuracy in the active tRNS condition for MI, SSVEP, and fused classifiers. (B) Pre- and post-intervention classification accuracy in the sham condition for MI, SSVEP, and fused classifiers. (C) Individual-level pre-to-post accuracy gain, calculated as post-intervention accuracy minus pre-intervention accuracy, across data lengths. Bars indicate the group mean gain, error bars denote the SEM, and individual dots represent participants. Light-colored curves indicate pre-intervention performance, whereas dark-colored curves indicate post-intervention performance. Red denotes active tRNS and blue denotes sham. The dashed horizontal line indicates chance-level accuracy at 50% in panels A and B, and zero gain in panel C. Shaded areas represent the SEM. Asterisks indicate within-condition pre-to-post differences ($p < 0.05$).

participants (Fig. 5C).

Following active tRNS, MI decoding accuracy increased significantly for cumulative windows ending at 3, 3.5, 4, 4.5, and 5 s (Fig. 5A). The corresponding mean improvements were 6.63, 7.08, 8.29, 7.67, and 6.33 percentage points, respectively ($q = 0.0490, 0.0299, 0.0201, 0.0201, \text{ and } 0.0281$). SSVEP and hybrid decoding also showed numerical post-intervention increases at several window endpoints, with the pattern being particularly apparent for hybrid decoding; however, none of these pre-to-post changes remained significant after correction for multiple comparisons.

During the sham session (Fig. 5B), decoding accuracy also increased numerically at several window endpoints, but no significant pre-to-post change was observed for MI, SSVEP, or hybrid decoding. Direct comparisons of the pre-to-post gains between active tRNS and sham showed numerically larger improvements following active stimulation, particularly for MI decoding. However, these between-condition gain differences did not reach statistical significance at any window endpoint or for any decoding modality. Thus, the most consistent post-intervention improvement was observed for MI

decoding within the active-tRNS session.

4 Discussion

The principal contribution of the present study is the systematic evaluation of high-frequency tRNS within a hybrid BCI MI and SSVEP. Previous neuromodulation studies involving MI–SSVEP hybrid BCIs have mainly focused on frequency-specific rhythmic stimulation, such as tACS [18,19]. To our knowledge, the present study is among the first to examine high-frequency tRNS in this context while characterizing its effects across multiple levels of BCI operation. By separating MI decoding, SSVEP decoding, oscillatory activity, and ERD/ERS responses, this component-level framework enabled stimulation-related effects on the two constituent modalities to be evaluated independently rather than inferred solely from changes in overall hybrid performance.

MI decoding performance improved within the active tRNS session, with the largest gains observed for cumulative analysis windows extending to 3–5 s after

task onset. This temporal profile is broadly consistent with previous evidence that high-frequency tRNS can modulate motor-cortical excitability through mechanisms involving altered membrane dynamics, changes in network responsiveness, and stochastic resonance [13,20,22,23,33]. Improvements in MI-related neural modulation and decoding performance have also been reported following other forms of transcranial electrical stimulation, with some studies showing more pronounced effects during later stages of MI, including the 3–5 s interval [15,51]. However, the difference in pre-to-post improvement between active and sham stimulation did not remain statistically significant after correction for multiple comparisons. The present findings therefore primarily indicate a within-session improvement in MI decoding under active tRNS.

The neurophysiological results provide complementary context for this decoding pattern. Representative ERD/ERS maps showed the expected hand-dependent modulation over sensorimotor regions, supporting the physiological validity of the MI paradigm. At the group level, mu-band power increased significantly from pre- to post-intervention during both baseline and task periods following active tRNS. This finding is consistent with previous reports that tRNS can modulate ongoing oscillatory activity [52]. Similar post-stimulation increases in EEG spectral power have also been reported following other forms of tES. Hermann et al. observed higher post-tDCS theta- and alpha-band power in responders, whereas Mangia et al. reported increases in alpha- and beta-band power during and after anodal tDCS [53,54]. These observations provide a broader electrophysiological context for the post-tRNS increase in mu-band power observed here and suggest that stimulation-related modulation may extend beyond task-evoked responses to the ongoing sensorimotor state preceding task onset.

ERD values also tended to become more negative following active stimulation, particularly over the contralateral motor cortex, although these changes did not reach statistical significance. The apparent dissociation between absolute spectral power and normalized ERD is not inherently contradictory, as the two measures characterize different aspects of oscillatory activity. ERD is defined relative to baseline power; consequently, a proportionally larger increase in baseline mu power than in task-period power can result in a more negative normalized ERD value even when absolute task-period power also increases. The ERD findings should therefore be regarded as exploratory neurophysiological evidence compatible with enhanced task-related desynchronization, rather than as independent confirmation of such an effect. Moreover, changes in conventional ERD amplitude and decoding performance are not necessarily expected to

show a one-to-one correspondence. Consistent with this interpretation, Xie et al. reported no significant post-TACS change in ERD during right-hand MI relative to the pre-stimulation condition, whereas MI classification accuracy increased from 83.01% to 88.19% [51]. This observation provides a relevant precedent for the pattern identified here and indicates that modest or statistically non-significant changes in ERD amplitude can coexist with measurable improvements in MI decoding, particularly when classification exploits spatially distributed information that is not fully captured by a single averaged ERD measure.

The component-level analysis further revealed a contrasting pattern for the SSVEP pathway. Under both stimulation conditions, responses at the target frequencies and their second harmonics were preserved across pre- and post-intervention recordings. In addition, the separation of the 34–35 Hz stimulation frequencies from the conventional mu range reduced potential spectral interference [12,30,31]. Neither SSVEP decoding accuracy nor the corresponding SNR and ITPC measures showed significant or observable intervention-related changes, indicating that the visually driven component remained comparatively stable across sessions. Hybrid decoding accuracy was numerically higher than MI decoding accuracy, consistent with the contribution of the relatively robust SSVEP component. However, a significant post-intervention improvement in hybrid performance was not established. At the 5-s endpoint, hybrid accuracy increased from 76.79% to 85.58% in the active session, corresponding to a gain of 8.79 percentage points, while an increase of 5.92 percentage points was also observed in the sham session. Thus, although active tRNS was accompanied by changes in MI decoding and mu-band activity, these changes were insufficient to produce a statistically demonstrable stimulation-specific improvement in overall hybrid decoding. This dissociation illustrates the value of component-level analysis in hybrid BCIs, as changes predominantly confined to one constituent modality may be attenuated when performance is assessed only at the level of the integrated decoder.

Several limitations should be considered. First, the cohort of young healthy adults was relatively small, which limits the generalizability of the findings. Larger and more heterogeneous samples are needed to establish the reproducibility of the observed effects and to determine whether their magnitude varies across individuals or populations. Second, this study employed an offline, open-loop paradigm and did not formally quantify blinding effectiveness, stimulation-related sensations, fatigue, or visual comfort. Future work should incorporate larger samples, quantitative assessments of blinding and tolerability, and online closed-loop hybrid

BCI control to determine whether the within-session improvements in MI decoding and the accompanying changes in mu-band activity observed here can translate into robust and reproducible benefits during real-time BCI operation. In addition, only a single stimulation session was administered in the present study, which may have influenced the modulatory effects to some extent. Future work will therefore also focus on repeated stimulation across longer observation periods [55–57].

5 Conclusions

This study evaluated Cz–Fpz high-frequency tRNS in an MI–SSVEP hybrid BCI using a component-specific, sham-controlled framework. MI decoding improved from pre- to post-intervention at longer time windows after active tRNS, whereas SSVEP decoding, SNR and ITPC remained generally stable. Fusion decoding was more accurate overall, but its pre-to-post improvement occurred in both active and sham sessions, and the between-condition difference was not significant. Thus, the observed MI improvement does not establish a stimulation-specific benefit. This component-level approach helps distinguish changes in individual BCI signals from changes in overall hybrid-BCI performance.

Data availability The datasets generated and/or analyzed during the current study are not publicly available due to ethical and participant privacy considerations but are available from the corresponding authors upon reasonable request.

Acknowledgments This work was supported in part by the National Natural Science Foundation of China under Grant 62471495, in part by the Tianjin Municipal Science and Technology Project under Grants 24JCJC00040 and 24JCZDJC00430, in part by the CAMS Innovation Fund for Medical Sciences under Grant 2025-I2M-TS-10, in part by the Laboratory of Advanced Medical Materials and Devices under Grant YGSKL2026ZZ01 and in part by the Non-profit Central Research Institute Fund of Chinese Academy of Medical Sciences under Grant 2024-JKCS-26.

Competing interests The authors declare no competing interests.

Compliance with ethics guidelines This study was approved by the Ethics Review Committee for Life Science and Medical Research Involving Humans, Institute of Biomedical Engineering, Chinese Academy of Medical Sciences (No. L2025-045-001).

References

1. Wolpaw J R, Birbaumer N, McFarland D J, et al. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 2002, 113(6): 767–791
2. Jin W J, Zhu X X, Qian L F, et al. Electroencephalogram-based adaptive closed-loop brain-computer interface in neurorehabilitation: a review. *Frontiers in Computational Neuroscience*, 2024, 18: 1431815
3. Lin Y H, Yuan Y, Chen J J, et al. Motor imagery combined with brain-computer interface for stroke patients: a meta-analysis. *Frontiers in Neurology*, 2026, 17: 1672882
4. Pfurtscheller G, Lopes da Silva F H. Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical Neurophysiology*, 1999, 110(11): 1842–1857
5. Vidaurre C, Blankertz B. Towards a cure for BCI illiteracy. *Brain Topography*, 2010, 23(2): 194–198
6. Vialatte F B, Maurice M, Dauwels J, et al. Steady-state visually evoked potentials: focus on essential paradigms and future perspectives. *Progress in Neurobiology*, 2010, 90(4): 418–438
7. Norcia A M, Appelbaum L G, Ales J M, et al. The steady-state visual evoked potential in vision research: a review. *Journal of Vision*, 2015, 15(6): 4
8. Azadi Moghadam M, Maleki A. Fatigue factors and fatigue indices in SSVEP-based brain-computer interfaces: a systematic review and meta-analysis. *Frontiers in Human Neuroscience*, 2023, 17: 1248474
9. Pfurtscheller G, Allison B Z, Brunner C, et al. The hybrid BCI. *Frontiers in Neuroscience*, 2010, 4: 30
10. Cheng L W, Li W Y, Liang L Y, et al. Hybrid BCI robotic arm control system based on MI and SSVEP. *Biomedical Signal Processing and Control*, 2025, 104: 107477
11. Zhang R Q, Li Z H, Pan X H, et al. Hybrid BCI for upper limb rehabilitation: integrating MI with peripheral field SSVEP stimulation. *Journal of Neuroscience Methods*, 2025, 423: 110537
12. Schrag E, Comaduran Marquez D, Kirton A, et al. An investigation into the comfort and neural response of textured visual stimuli in pediatric SSVEP-based BCI. *Scientific Reports*, 2025, 15(1): 26168
13. Antal A, Herrmann C S. Transcranial alternating current and random noise stimulation: possible mechanisms. *Neural Plasticity*, 2016, 2016: 3616807
14. McNally M, Byczynski G, Vanneste S. An overview of the effects and mechanisms of transcranial stimulation frequency on motor learning. *Journal of NeuroEngineering and Rehabilitation*, 2024, 21(1): 157
15. Wei P F, He W, Zhou Y, et al. Performance of motor imagery brain-computer interface based on anodal transcranial direct current stimulation modulation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2013, 21(3): 404–415
16. Ang K K, Guan C T, Phua K S, et al. Facilitating effects of transcranial direct current stimulation on motor imagery brain-computer interface with robotic feedback for stroke rehabilitation. *Archives of Physical Medicine and Rehabilitation*, 2015, 96(S3): S79–S87
17. Xi L, Liu Q, Li H, et al. Comparative efficacy of motor imagery augmented with central non-invasive brain stimulation versus peripheral electrical stimulation for upper extremity rehabilitation post-stroke: a systematic review and network meta-analysis. *Journal of NeuroEngineering and Rehabilitation*, 2026, 23(1): 186
18. Lim R Y, Ang K K, Chew E, et al. A review on motor imagery with transcranial alternating current stimulation: bridging motor and cognitive welfare for patient rehabilitation. *Brain Sciences*,

- 2023, 13(11): 1584
19. Li Z H, Zhang R Q, Li W J, et al. Enhancement of hybrid BCI system performance based on motor imagery and SSVEP by transcranial alternating current stimulation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2024, 32: 3222–3230
 20. Terney D, Chaieb L, Moliadze V, et al. Increasing human brain excitability by transcranial high-frequency random noise stimulation. *The Journal of Neuroscience*, 2008, 28(52): 14147–14155
 21. van der Groen O, Wenderoth N. Transcranial random noise stimulation of visual cortex: stochastic resonance enhances central mechanisms of perception. *The Journal of Neuroscience*, 2016, 36(19): 5289–5298
 22. van der Groen O, Potok W, Wenderoth N, et al. Using noise for the better: the effects of transcranial random noise stimulation on the brain and behavior. *Neuroscience & Biobehavioral Reviews*, 2022, 138: 104702
 23. Potok W, van der Groen O, Bächinger M, et al. Transcranial random noise stimulation modulates neural processing of sensory and motor circuits, from potential cellular mechanisms to behavior: a scoping review. *eNeuro*, 2022, 9(1): ENEURO.0248–21.2021
 24. Brancucci A, Rivolta D, Nitsche M A, et al. The effects of transcranial random noise stimulation on motor function: a comprehensive review of the literature. *Physiology & Behavior*, 2023, 261: 114073
 25. Ke S C, Lo Y H, Tseng P. No frequency-specific effect of transcranial random noise stimulation on resting EEG. *Journal of Integrative Neuroscience*, 2024, 23(3): 59
 26. Sethi A, Pascual-Leone A, Santarnecchi E, et al. Transcranial random noise stimulation to augment hand function in individuals with moderate-to-severe stroke: a pilot randomized clinical trial. *Restorative Neurology and Neuroscience*, 2024, 41(5-6): 193–202
 27. Paulus W. Transcranial electrical stimulation (tES-tDCS; tRNS, tACS) methods. *Neuropsychological Rehabilitation*, 2011, 21(5): 602–617
 28. Hong K S, Khan M J. Hybrid brain-computer interface techniques for improved classification accuracy and increased number of commands: a review. *Frontiers in Neurorobotics*, 2017, 11: 35
 29. Wierzgała P, Zapala D, Wójcik G M, et al. Most popular signal processing methods in motor-imagery BCI: a review and meta-analysis. *Frontiers in Neuroinformatics*, 2018, 12: 78
 30. Ladouce S, Darmet L, Torre Tresols J J, et al. Improving user experience of SSVEP BCI through low amplitude depth and high frequency stimuli design. *Scientific Reports*, 2022, 12(1): 8865
 31. Gu M, Pei W H, Gao X R, et al. An open dataset for human SSVEPs in the frequency range of 1–60 Hz. *Scientific Data*, 2024, 11(1): 196
 32. Yang Y J, Jeon E J, Kim J S, et al. Characterization of kinesthetic motor imagery compared with visual motor imageries. *Scientific Reports*, 2021, 11(1): 3751
 33. Moret B, Donato R, Nucci M, et al. Transcranial random noise stimulation (tRNS): a wide range of frequencies is needed for increasing cortical excitability. *Scientific Reports*, 2019, 9(1): 15150
 34. Bikson M, Grossman P, Thomas C, et al. Safety of transcranial direct current stimulation: evidence based update 2016. *Brain Stimulation*, 2016, 9(5): 641–661
 35. Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 2004, 134(1): 9–21
 36. Widmann A, Schröger E, Maess B. Digital filter design for electrophysiological data—a practical approach. *Journal of Neuroscience Methods*, 2015, 250: 34–46
 37. Perrin F, Pernier J, Bertrand O, et al. Spherical splines for scalp potential and current density mapping. *Electroencephalography and Clinical Neurophysiology*, 1989, 72(2): 184–187
 38. Lee T W, Girolami M, Sejnowski T J. Independent component analysis using an extended Infomax algorithm for mixed subgaussian and supergaussian sources. *Neural Computation*, 1999, 11(2): 417–441
 39. Pion-Tonachini L, Kreutz-Delgado K, Makeig S. ICLABEL: an automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, 2019, 198: 181–197
 40. Nakanishi M, Wang Y J, Chen X G, et al. Enhancing detection of SSVEPs for a high-speed brain speller using task-related component analysis. *IEEE Transactions on Biomedical Engineering*, 2018, 65(1): 104–112
 41. Hu L, Xiao P, Zhang Z G, et al. Single-trial time–frequency analysis of electrocortical signals: baseline correction and beyond. *NeuroImage*, 2014, 84: 876–887
 42. Marshall P J, Young T, Meltzoff A N. Neural correlates of action observation and execution in 14-month-old infants: an event-related EEG desynchronization study. *Developmental Science*, 2011, 14(3): 474–480
 43. Saby J N, Marshall P J, Meltzoff A N. Neural correlates of being imitated: an EEG study in preverbal infants. *Social Neuroscience*, 2012, 7(6): 650–661
 44. Ang K K, Chin Z Y, Wang C C, et al. Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b. *Frontiers in Neuroscience*, 2012, 6: 39
 45. Lotte F, Guan C T. Regularizing common spatial patterns to improve BCI designs: unified theory and new algorithms. *IEEE Transactions on Biomedical Engineering*, 2011, 58(2): 355–362
 46. Varma S, Simon R. Bias in error estimation when using cross-validation for model selection. *BMC Bioinformatics*, 2006, 7(1): 91
 47. White J, Power S D. k-Fold cross-validation can significantly over-estimate true classification accuracy in common EEG-based passive BCI experimental designs: an empirical investigation. *Sensors*, 2023, 23(13): 6077
 48. Benjamini Y, Hochberg Y. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 1995, 57(1): 289–300
 49. Benjamini Y, Bogomolov M. Selective inference on multiple families of hypotheses. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 2014, 76(1): 297–318
 50. Noble W S. How does multiple testing correction work? *Nature*

- Biotechnology, 2009, 27(12): 1135–1137
51. Xie J X, Peng M Q, Lu J Q, et al. Enhancement of event-related desynchronization in motor imagery based on transcranial electrical stimulation. *Frontiers in Human Neuroscience*, 2021, 15: 635351
 52. Ghin F, O'Hare L, Pavan A. Electrophysiological aftereffects of high-frequency transcranial random noise stimulation (hf-tRNS): an EEG investigation. *Experimental Brain Research*, 2021, 239(8): 2399–2418
 53. Hermann B, Raimondo F, Hirsch L, et al. Combined behavioral and electrophysiological evidence for a direct cortical effect of prefrontal tDCS on disorders of consciousness. *Scientific Reports*, 2020, 10(1): 4323
 54. Mangia A L, Pirini M, Cappello A. Transcranial direct current stimulation and power spectral parameters: a tDCS/EEG co-registration study. *Frontiers in Human Neuroscience*, 2014, 8: 601
 55. Brambilla M, Dinkelbach L, Bigler A, et al. The effect of transcranial random noise stimulation on cognitive training outcome in healthy aging. *Frontiers in Neurology*, 2021, 12: 625359
 56. Dakwar-Kawar O, Mairon N, Hochman S, et al. Transcranial random noise stimulation combined with cognitive training for treating ADHD: a randomized, sham-controlled clinical trial. *Translational Psychiatry*, 2023, 13(1): 271
 57. Wei J W, Zou H R, Tang Q Y, et al. Enhancing visual perception by modulating prestimulus alpha and beta power with tRNS. *Communications Biology*, 2025, 8(1): 1182