Multimodal Brain–Computer Interface Grand Challenge: EEG–fNIRS based Handwriting-Trajectory Classification

Abstract

We propose an ACM Multimedia Grand Challenge on multimodal brain–computer interfaces (BCIs) that targets a single, well-defined task: four-class classification of imagined logographic handwriting using synchronized electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS). The challenge is built on a multi-session EEG–fNIRS benchmark with aligned trial annotations and standardized preprocessing, enabling reproducible comparison of temporal modeling and multimodal fusion methods under realistic session variability. We define one track with a unified model-submission format, and all evaluation is performed automatically on a hidden test set by the organizers. The leaderboard is ranked solely by overall classification accuracy (ACC). We commit to maintaining the public challenge website, starter kit, and evaluation infrastructure for at least three years.

Keywords

Grand Challenge, Brain–Computer Interface, EEG, fNIRS, Multimodal Learning, Imagined Handwriting, Classification

1 Introduction

Brain–computer interface (BCI) enables direct human–computer interaction by decoding neural activity into machine commands, with broad potential in communication and rehabilitation [2, 10]. In particular, non-invasive BCIs are attractive due to their low risk and cost-effectiveness, and motor imagery (MI) has become a widely studied paradigm because MI-based training can support stroke rehabilitation [1]. Beyond classical limb MI, *handwriting trajectory MI* aims to infer imagined writing movements and thus offers a natural route towards brain-to-text communication for people with severe paralysis [6, 9].

Despite rapid progress, two gaps limit current trajectory-MI research. First, most studies focus on *phonetic* languages, while *logographic* writing remains under-explored [8]. Compared with phonetic scripts, logographic characters (e.g., Chinese) often convey rich semantics with fewer symbols and exhibit more complex spatiotemporal stroke structures, posing a harder benchmark for sequence modeling and representation learning [11]. Yet, trajectory-MI decoding results are still largely demonstrated on phonetic alphabets [6, 9], leaving a clear need for standardized evaluation on logographic writing.

Second, existing trajectory-MI datasets predominantly rely on a *single* neural modality (often electrical recordings) [5, 7]. However, brain dynamics are complex and informative features may be missed when using only one sensing type. Hybrid neuroimaging that combines electroencephalography (EEG) with functional near-infrared spectroscopy (fNIRS) can capture complementary electrophysiological and hemodynamic responses to the same underlying neural processes [3, 4]. This motivates a multimodal benchmark for trajectory MI with synchronized EEG–fNIRS, which remains scarce in resources.

To address these gaps and enable fair comparison, we propose an ACM Multimedia Grand Challenge on **EEG–fNIRS imagined logographic handwriting classification**. The competition provides a unified task definition, fixed splits, standardized preprocessing, and hidden-test evaluation, and thus encourages reproducible advances in temporal modeling and multimodal fusion under realistic session variability.

2 Motivation and Importance

EEG captures fast electrophysiological dynamics with millisecond resolution, whereas fNIRS provides complementary hemodynamic information that reflects slower vascular responses. Their combination offers a realistic multimodal learning setting in which models must integrate heterogeneous signals with different noise characteristics and temporal profiles. From a multimedia perspective, reliable imagined handwriting decoding can support assistive communication and intent-aware interaction, and it encourages methods that learn discriminative spatiotemporal representations rather than relying on static features. A Grand Challenge format supports fair comparison by standardizing the task definition, the data splits, and the evaluation pipeline, while keeping the test labels hidden to reduce evaluation ambiguity and leakage.

3 Challenge Task

We define a single track that evaluates a model's ability to classify imagined handwriting trials into one of four logographic character classes using synchronized EEG–fNIRS recordings. Each trial contains paired EEG and fNIRS segments aligned to the same cue, and the goal is to predict the correct class label for every test trial.

3.1 Input and Output

The organizers provide synchronized EEG and fNIRS time series with trial identifiers and metadata, together with official preprocessing scripts and trial definitions. A submitted model must take a set of trials as input and output one predicted class label per trial in the required format. To keep the challenge focused and comparable across teams, the task is evaluated only in the full-modality setting using both EEG and fNIRS.

3.2 Track Rules

Participants must train using only the released training data and labels. Unlabeled use of the released training split for self-supervised representation learning is allowed, but external labeled datasets are not permitted. Any additional heuristics that rely on access to test labels are disallowed, and the final ranking is determined by automatic evaluation on a hidden test set.

4 Dataset and Resources

The benchmark dataset contains synchronized EEG and fNIRS recordings collected under an imagined handwriting motor imagery paradigm with four logographic character classes and multiple sessions over two consecutive days, with aligned event markers and standardized trial annotations. EEG is recorded with a multi-channel cap following a standard head-surface positioning system. fNIRS is recorded with dual-wavelength measurements and provided in hemodynamic representations. The dataset is released with a fixed split so that results are comparable and reproducible across methods.

We will provide a starter kit that includes data loaders, reference preprocessing implementations for both modalities, and baseline models that establish expected performance for unimodal encoders and simple fusion approaches. The starter kit also includes an inference template matching the submission API, allowing teams to validate that their models run correctly before submission.

5 Submission and Evaluation

5.1 Model Submission

Participants submit a runnable model package in the official format specified by the organizers. Submissions are required to implement a standard inference interface that reads the test trials and outputs predicted labels. This design reduces ambiguity in evaluation and ensures that all models are assessed under the same runtime assumptions.

5.2 Evaluation on Hidden Test Set

All evaluation is performed by the organizers on a hidden test set. Participants do not receive test labels, and they do not need to run any evaluation code themselves. The submission server executes each model, collects its predictions, and computes the official metric automatically.

5.3 Metric

The leaderboard is ranked solely by overall classification accuracy (ACC) on the hidden test set.

$$\mathrm{ACC} = \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(\hat{y}_i = y_i)\,, \tag{1}$$

where N is the number of test trials, y_i is the ground-truth label, $\hat{y}_i$ is the predicted label, and $\mathbb{I}(\cdot)$ is an indicator function that equals 1 if the condition holds and 0 otherwise.

6 Website, Dissemination, and Multi-Year Commitment

We commit to maintaining a public challenge website, leaderboard, starter kit, and evaluation infrastructure for at least three years. The website will host the task definition, data access instructions, baseline code, submission format documentation, and an archive of winning solutions and technical reports. We will publicize the challenge through ACMMM channels and relevant communities in multimodal learning, physiological signal processing, HCI, and neuroimaging.

7 Timeline

Data, baseline paper & code available	20 April, 2026
Results submission start	20 June, 2026
Results submission deadline	1 July, 2026
Deadline for paper submission	15 July, 2026
Paper acceptance notification	30 July, 2026
Deadline for camera-ready papers	06 August, 2026

8 People

8.1 Chairs

Badong Chen received the B.S. and M.S. degrees in control theory and engineering from Chongqing University, in 1997 and 2003, respectively, and the Ph.D. degree in computer science and technology from Tsinghua University in 2008. He was a Postdoctoral Researcher with Tsinghua University from 2008 to 2010, and a Postdoctoral Associate at the University of Florida Computational NeuroEngineering Laboratory (CNEL) during the period October, 2010 to September, 2012. In 2015, he visited the Nanyang Technological University (NTU) as a visiting research scientist. He also served as a senior research fellow with The Hong Kong Polytechnic University in 2017. Currently he is a professor at the Institute of Artificial Intelligence and Robotics (IAIR), Xi'an Jiaotong University. His current research interests are in machine learning, brain machine interfaces and brain inspired intelligence. He has published 7 books, 5 chapters, and over 300 papers in various journals and conference proceedings. Dr. Chen is an IEEE Senior Member and serves (or has served) as a Technical Committee Member of IEEE SPS Machine Learning for Signal Processing (MLSP), and a Technical Committee Member of IEEE CIS Cognitive and Developmental Systems (CDS), and an Associate Editor (or Editor Board Member) for several international journals including IEEE Transactions on Circuits and Systems for Video Technology (TCSVT), IEEE Transactions on Neural Networks and Learning Systems (TNNLS), IEEE Transactions on Cognitive and Developmental Systems (TCDS), Neural Networks, Journal of The Franklin Institute, and Entropy.

Ziyu Jia is an Assistant Professor at the Institute of Automation, Chinese Academy of Sciences. His research focuses on time-series analysis methods and their applications in health and medicine, including multimodal affective computing, sleep stage classification, and brain-computer interfaces. He has published over 50 peer-reviewed papers in venues such as IEEE Transactions on Affective Computing, IEEE Transactions on Multimedia, IEEE Transactions on Neural Systems and Rehabilitation Engineering, KDD, and ICLR. Dr. Jia currently serves as an Associate Editor or Editorial Board Member for prestigious journals, including IEEE Transactions on Affective Computing and Information Fusion, and he is an Area

Chair for major AI and machine learning conferences such as IJCAI and IJCNN. In addition to his academic contributions, Dr. Jia has extensive industry experience, having successfully led multiple R&D projects and secured several patents. He has received numerous honors, including the MSRA StarTrack Award and the CIE Young Talent Award.

Roger Mark is a Professor at MIT whose research advances healthcare through physiologic signal processing, data science, and machine learning. He leads the NIH supported PhysioNet project, providing open access to large scale physiologic signal databases and software. His Critical Care Informatics initiative develops high resolution ICU and ED datasets that include EHRs, waveforms, and imaging, now used by many researchers worldwide. Dr. Mark is an advocate for open data to accelerate medical artificial intelligence research and to enhance clinical decision making in intensive care settings.

8.2 Co-Chairs

Jing Wang (Senior Member, IEEE) received the Ph.D. degree in statistics from Beijing Jiaotong University, Beijing, China, in 2015. She is a Professor with the School of Computer Science and Technology, Beijing Jiaotong University. Her primary research interests include Brain-Computer Interface (BCI), Time Series Analysis and Mining, Anomaly Detection, and Machine Learning, with a particular focus on applications in healthcare, transportation, and financial big data.

Tianzi Jiang is Professor and Director of Beijing Key Laboratory of Brainnetome, Director of the Brainnetome Center, the Institute of Automation of the Chinese Academy of Sciences, the core member of CAS Center for Excellence in Brain Science and Intelligence Technology, and Professor of Queensland Brain Institute, University of Queensland. He received a Ph.D. degree in computational mathematics from Zhejiang University in 1994. After he graduated, he worked as a postdoctoral research fellow (1994–1996) and Associate Professor (1996–1999), and full professor (1999–present) at his current institution in China. During that time, he worked as a Vice-Chancellor's postdoctoral fellow at the University of New South Wales, a visiting scientist at the Max Planck Institute for Human Cognitive and Brain Sciences, a research fellow at the Queen's University of Belfast, and a visiting professor at the University of Houston. He is also a Professor at the University of Queensland, Australia, and an Adjunct Professor at the University of Electronic Science and Technology of China, and Zhejiang University. He served and is serving as the Chair and Program Committee member of a number of international conferences, including General Chair of MICCAI'2010. He was awarded the National Distinguished Youth Foundations by the Chinese Government (2004), the Natural Science Award of China (2004), and the Natural Science Award of the Chinese Academy of Sciences (1996).

Hengguan Huang is an Assistant Professor in the Department of Public Health, Section for Health Data Science and AI, at the University of Copenhagen. He received his PhD in Machine Learning from the School of Computing, National University of Singapore. His research aims to develop AI technologies that are not only powered by big data and large models but are also deeply grounded in scientific principles and aligned with societal values.

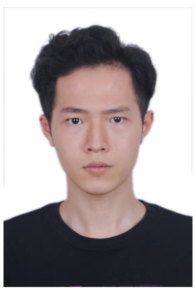
8.3 Dataset Track Chair

Xinliang Zhou received his Ph.D. degree in computer science from Nanyang Technological University, Singapore, in 2025. His research has been published in highly selective venues, such as the International Conference on Learning Representations and the IEEE Journal of Biomedical and Health Informatics. He also regularly serves as a program committee member for major international AI conferences. His research interests include brain–computer interfaces, brain foundation models, and interpretable artificial intelligence.

Jingying Ma is a PhD student at the Saw Swee Hock School of Public Health, National University of Singapore. She received her B.E. degree in Computer Science (major) and B.S. degree in Mathematics and Applied Mathematics (minor) from Beihang University, China, in 2023. Her current research interests include medical time series analysis and brain foundation models.

8.4 Technical Committee Chair

Hairong Chen is a Research Assistant at the Institute of Automation, Chinese Academy of Sciences. He is currently studying Artificial Intelligence at Beijing Jiaotong University, Beijing, China. His research interests include Brain-Computer Interfaces and Large Language Models.



Chenyu Liu received the B.E. degree in software engineering from University of Electronic Science and Technology of China, Sichuan, China, in 2020. He is currently working toward the Ph.D. degree with the College of Computing and Data Science, Nanyang Technological University, Singapore. His research interests include Brain-Computer Interfaces, Brain Foundation Model, and NeuroAI.

9 Ethical Statement

The local Institutional Review Board approved the ethical conduct of this study. All procedures involving human participants strictly adhered to established ethical standards, with particular emphasis on ensuring participant safety, privacy, and informed consent. Prior to participation, all subjects were fully informed about the study's purpose, procedures, and data usage policies.

10 Commitment

If our proposal is accepted, we commit to publishing and maintaining a website dedicated to the Grand Challenge, which will contain all relevant information, datasets, and tasks for at least the next three years. We also pledge to collaborate with the ACM Multimedia Conference organizers to publicize the Grand Challenge tasks and encourage researcher participation. For any questions, please contact Ziyu Jia (jia.ziyu@outlook.com).

References

[1] María A. Cervera, Surjo R. Soekadar, Junichi Ushiba, José del R. Millán, Meigen Liu, Niels Birbaumer, and Gangadhar Garipelli. 2018. Brain-computer interfaces for post-stroke motor rehabilitation: a meta-analysis. *Annals of Clinical and Translational Neurology* 5, 5 (2018), 651–663. doi:10.1002/acn3.544

[2] Ujwal Chaudhary, Niels Birbaumer, and Ander Ramos-Murguialday. 2016. Brain–computer interfaces for communication and rehabilitation. *Nature Reviews Neurology* 12, 9 (Sept. 2016), 513–525. doi:10.1038/nrneurol.2016.113

[3] Siamac Fazli, Jan Mehnert, Jens Steinbrink, Gabriel Curio, Arno Villringer, Klaus-Robert Müller, and Benjamin Blankertz. 2012. Enhanced performance by a hybrid NIRS–EEG brain computer interface. *NeuroImage* 59, 1 (2012), 519–529. doi:10.1016/j.neuroimage.2011.07.084 Neuroergonomics: The human brain in action and at work.

[4] Ziming Liu, Jeremy Shore, Miao Wang, Fengpei Yuan, Aaron Buss, and Xiaopeng Zhao. 2021. A systematic review on hybrid EEG/fNIRS in brain-computer interface. *Biomedical Signal Processing and Control* 68 (2021), 102595. doi:10.1016/j.bspc.2021.102595

[5] David O. Nahmias and Kimberly L. Kontson. 2020. Easy Perturbation EEG Algorithm for Spectral Importance (easyPEASI): A Simple Method to Identify Important Spectral Features of EEG in Deep Learning Models. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (Virtual Event, CA, USA) *(KDD '20)*. Association for Computing Machinery, New York, NY, USA, 2398–2406. doi:10.1145/3394486.3403289

[6] Chethan Pandarinath, Paul Nuyujukian, Christine H. Blabe, Brittany L. Sorice, Jad Saab, Francis R. Willett, Leigh R. Hochberg, Krishna V. Shenoy, and Jaimie M. Henderson. 2017. High performance communication by people with paralysis using an intracortical brain-computer interface. *eLife* 6 (Feb. 2017), e18554. doi:10.7554/eLife.18554

[7] Daniel B. Rubin and Leigh R. Hochberg. 2023. BrainGate: An Intracortical Brain-Computer Interface for the Restoration of Communication and Functional Independence for People with Paralysis. In *2023 11th International Winter Conference on Brain-Computer Interface (BCI)*. 1–3. doi:10.1109/BCI57258.2023.10078547

[8] Richard Sproat and Alexander Gutkin. 2021. The Taxonomy of Writing Systems: How to Measure How Logographic a System Is. *Computational Linguistics* 47, 3 (Nov. 2021), 477–528. doi:10.1162/coli_a_00409

[9] Francis R. Willett, Donald T. Avansino, Leigh R. Hochberg, Jaimie M. Henderson, and Krishna V. Shenoy. 2021. High-performance brain-to-text communication via handwriting. *Nature* 593, 7858 (May 2021), 249–254. doi:10.1038/s41586-021-03506-2

[10] Jonathan R Wolpaw, Niels Birbaumer, Dennis J McFarland, Gert Pfurtscheller, and Theresa M Vaughan. 2002. Brain–computer interfaces for communication and control. *Clinical Neurophysiology* 113, 6 (2002), 767–791. doi:10.1016/S1388-2457(02)00057-3

[11] Xu-Yao Zhang, Yoshua Bengio, and Cheng-Lin Liu. 2017. Online and offline handwritten Chinese character recognition: A comprehensive study and new benchmark. *Pattern Recognition* 61 (2017), 348–360. doi:10.1016/j.patcog.2016.08.005